Comparison of Stochastic Streamflow Generators and the use thereof within the Water Resources Yield Model and MIKE Hydro Basin

by

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Declaration

I, Lourens Francois Maass, declare that all the work done in this thesis is my own, original work and I accept the copyright thereof. This thesis has not previously been submitted for the purpose of receiving any qualification.

Signed: ....

Date: December 2017

Abstract

The development and improvement of hydrological simulation software models is a continuous process. These software models, together with hydrological stochastic data generators enhances the ability to analyse a hydrological system and determine its reliability. Many different stochastic generators exist, but the two that are of interest in this research are monthly streamflow generators, namely STOMSA and SAMS.

STOMSA is a stochastic streamflow generator developed for the Department of Water and Sanitation of South Africa, while SAMS is a stochastic streamflow generator developed in the United States of America. Both these generators are able to generate satisfying stochastic streamflow data, with the only concern being a high variance between the average annual streamflows of the different stochastic sequences generated by SAMS.

Over time stochastic data generators became part of the hydrological analysis process. This led to the incorporation of stochastic data generators into hydrological simulation models. As is the case for stochastic streamflow generators many different hydrological simulation models are available, but the two that are of interest in this research are the WRYM and MIKE Hydro Basin.

The WRYM is the hydrological simulation software model used by the Department of Water and Sanitation of South Africa. The model is used to do hydrological yield analyses for hydrological systems in South Africa. MIKE Hydro Basin is a hydrological simulation software model developed by the Danish Hydraulic Institute (DHI).

The WRYM is able to do automated historical yield analyses and can calculate the historical firm yield of a hydrological system accurately. The WRYM also uses STOMSA as a built-in stochastic streamflow generator and uses the data generated by STOMSA to do a reliability of supply analysis for a hydrological system. MIKE Hydro Basin, however, is not able to generate stochastic streamflow data or do system yield analyses. It is used to simulate hydrological systems.

When the practicality of the two models is considered, it is argued that MIKE Hydro Basin is more user-friendly than the WRYM. The WRYM is very technical and difficult to use without proper training or assistance. It should also be noted that the WRYM, , makes possible calculation errors in the reliability of supply analysis and results should be used with caution.

Opsomming

Die ontwikkeling en verbetering van hidrologiese simulasie sagteware modelle is 'n deurlopende proses. Hierdie sagteware modelle tesame met hidrologiese stogastiese data generators dra by tot die vermoë om 'n hidrologiese stelsel te ontleed en die betroubaarheid vir die stelsel om water te lewer, te bepaal. Daar bestaan 'n wye reeks verskillende stogastiese generators, maar die twee wat van belang is in hierdie navorsing is die maandelikse stroomvloei generators, naamlik STOMSA en SAMS.

STOMSA is 'n stogastiese stroomvloei generator wat ontwikkel is vir die Departement van Water en Sanitasie van Suid-Afrika, terwyl SAMS ontwikkel is in die Verenigde State van Amerika. Beide hierdie generators is in staat om bevredigende stogastiese stroomvloei data te genereer. Die enigste bekommernis is 'n hoë afwyking tussen die gemiddelde jaarlikse stroomvloeie van die verskillende stogastiese reekse wat deur SAMS gegenereer is.

Stogastiese data generators het met die verloop van tyd deel geword van die hidrologiese ontledingsproses. Dit het gelei tot die insluiting van stogastiese data generators in hidrologiese simulasie modelle. Daar bestaan 'n wye reeks verskillende hidrologiese simulasie modelle, maar die twee wat van belang is in hierdie navorsing is die WRYM en Mike Hydro Basin.

Die WRYM is 'n hidrologiese simulasie sagteware model wat gebruik word deur die Departement van Water en Sanitasie van Suid-Afrika. Die model word gebruik om hidrologiese leweringsontledings vir hidrologiese stelsels in Suid-Afrika te doen, terwyl MIKE Hydro Basin ontwikkel is deur die Danish Hydraulic Institute (DHI).

Die WRYM is in staat om die historiese veilige lewering van 'n hidrologiese stelsel akkuraat te bereken. Die WRYM gebruik ook STOMSA as 'n interne stogastiese stroomvloei generator, en gebruik die gegenereerde data om 'n betroubaarheidsontleding vir 'n hidrologiese stelsel te doen. MIKE Hydro Basin is egter nie in staat om stogastiese stroomvloei data te genereer of die lewerings van 'n stelsel te ontleed nie, en word slegs gebruik om hidrologiese stelsels te simuleer.

Wanneer die praktiese funksionaliteit van die twee modelle oorweeg word, blyk dit dat MIKE Hydro Basin meer gebruikersvriendelik is as die WRYM. Die WRYM is baie tegnies en moeilik om te gebruik sonder behoorlike opleiding. Dit moet ook in ag geneem word dat die WRYM moontleke foute maak met die berekening van die betroubaarheid van 'n stelsel en resultate moet dus versigtig hanteer word.

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Dedications

I would like to dedicate this thesis to my father, Leon Maass, my mother, Leroena Maass, and my three sisters, Corné Maass, Joánie Maass and Rouxné Maass. Without their continuous love and support throughout my six years of study, I would not have been able to complete my studies and achieve my goals.

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Chapter 1

Introduction

1.1 Overview

Water has always and will always be one of the most crucial resources of the world in order to sustain life. The need for water drives the continuous development of reliable water storage (e.g. reservoirs) and transportations systems.

Over the years multiple hydrological simulation software models have been developed and are used in practice to simulate real life hydrological events, such as the rainfall over a catchment and the runoff into a reservoir, the infiltration of water into the sediment in the reservoir and evaporation from the reservoir surface, up to the abstraction of water from the reservoir by a water user. These three hydrological events are simple examples of what these simulation models are capable of, but forms the cornerstone of hydrological engineering as we know it today.

The development of hydrological simulation software models is, however, not the only progress made in the hydrology and a number of experts have made contributions by developing mathematical models used for calculating stochastic hydrological data, such as rainfall, climate and streamflows. Stochastic hydrological data is data calculated from an observed historical data set to create a new set of completely random data that has more or less the same statistical characteristics as the historical data set.

When historical hydrological data is used in a hydrological simulation model, the results are based only on the realisation of past hydrological data. Stochastic hydrological data provides alternative realisations that are equally likely to occur and creates the opportunity to analyse a hydrological system on what could possibly happen in the future rather than only what had happened in the past.

The establishment of mathematical stochastic models escalated into the development of hydrological stochastic data generation software that uses these mathematical models to generate large amounts of stochastic data sequences. These stochastic data generators, coupled with the hydrological simulation models vastly enhanced the ability to determine the reliability of a hydrological system more accurately.

In this thesis two stochastic streamflow generators were identified namely the Stochastic Analysis, Modelling and Simulation model (SAMS) and the Stochastic Model of South Africa (STOMSA).

The Stochastic Analysis, Modelling and Simulation model (SAMS) is a stochastic streamflow generator developed by the Colorado State University and the U.S. Bureau of Reclamation. SAMS was used for hydrological projects in Canada, South America, South Korea and Switzerland and the United States of America. SAMS was, however, never used in hydrological projects in South Africa.

STOMSA is the stochastic streamflow generator commonly known and used in hydrological projects in South Africa and is incorporated in the Water Resource Yield Model (WRYM). The WRYM is a network-based hydrological simulation model developed and used by the the Department of Water and Sanitation of South Africa. STOMSA and the WRYM are used in most hydrological projects in South Africa.

MIKE Hydro Basin is another hydrological simulation model identified in this thesis. MIKE Hydro Basin is used in South Africa as well as other countries all over the world and was developed by the Danish Hydraulic Institute (DHI).

1.2 Aim

The aim of this thesis was to evaluate the two stochastic streamflow generators, SAMS and STOMSA identified in Section 1.1, and to determine if there is a difference between two stochastic streamflow generators that were developed in different countries with different climate conditions and therefore it is important to compare SAMS and STOMSA on a technical as well as practical level.

This thesis also aims to evaluate how the two hydrological simulation models, WRYM and MIKE Hydro Basin identified in Section 1.1, use stochastic streamflow data in their respective hydrological analysis processes. The WRYM and MIKE Hydro Basin are both hydrological simulation models used in South Africa and it is therefore important to compare the WRYM and MIKE Hydro Basin on a technical as well as practical level. It is expected that both models would present the same results, since both models are commercially used and tested. However, both models were developed in different countries with different protocols and therefore some differences may exist.

1.3 Thesis Statement

In this thesis the two stochastic streamflow generators, STOMSA and SAMS, were evaluated and compared on a technical as well as practical level. The two hydrological simulation models, the WRYM and MIKE Hydro Basin, are also evaluated and compared as to how the two models use stochastic streamflow data on a technical as well as practical level. For the comparison of the WRYM and MIKE Hydro Basin, stochastic streamflow data generated by STOMSA was used for consistency.

Chapter 2

Literature Review

2.1 Hydrologic Modelling

Hydrology is the study of the manner in which water moves through the hydrological cycle and the way in which constituents such as pollutants and sediments are transported in the water as it flows (Maidment, 1996). In order to understand and make sense of hydrology certain hydrologic models and systems were developed.

Hydrologic systems are extremely complex and Xu (2002) states that it is not possible for mankind to fully understand them. He further states that catchment hydrologic models have been developed over the years for various reasons and, therefore, assume many different forms. Dooge (1968) defines a hydrological system as a set of chemical, physical, and/or biological processes that acts upon input variables in order to convert them into output variables. He further defines a model as a simplified representation of a complex system. Hydrological models can either be physical, for example a scaled-down version of the full-scale prototype (Chow, 1967); or an analogue, like the resistance-capacitance analogue of a complete catchment which was used by Ishihara et al. (1961); or mathematical, where the behaviour of the system is represented by a set of equations, and together with logical statements can express the relationships between variables and parameters (Clarke, 1973).

According to Xu (2002) these models are designed to meet certain primary objectives. The one primary objective is to gain a better understanding of hydrological features operating within a catchment and of how changes in the catchment may affect these features. Another objective of catchment modelling is to generate synthetic sequences of hydrological data which can be used to facilitate design for forecasting purposes. These sequences are also valuable for the studying of potential impacts of variables in climate or land use. The variety of uses for hydrological models and the rapid increase in both technical support and scientific understanding, from data collection processes and computer technology, have already produced a huge amount of sophistication.

2.1.1 Classification of Hydrologic Models

Many different ways exist to classify hydrological models. One method which is commonly used is that of Singh (1988) that is presented by Xu (2002) in which hydrologic models were categorised as material and symbolic models. A breakdown of this classification is presented in Figure 2.1.

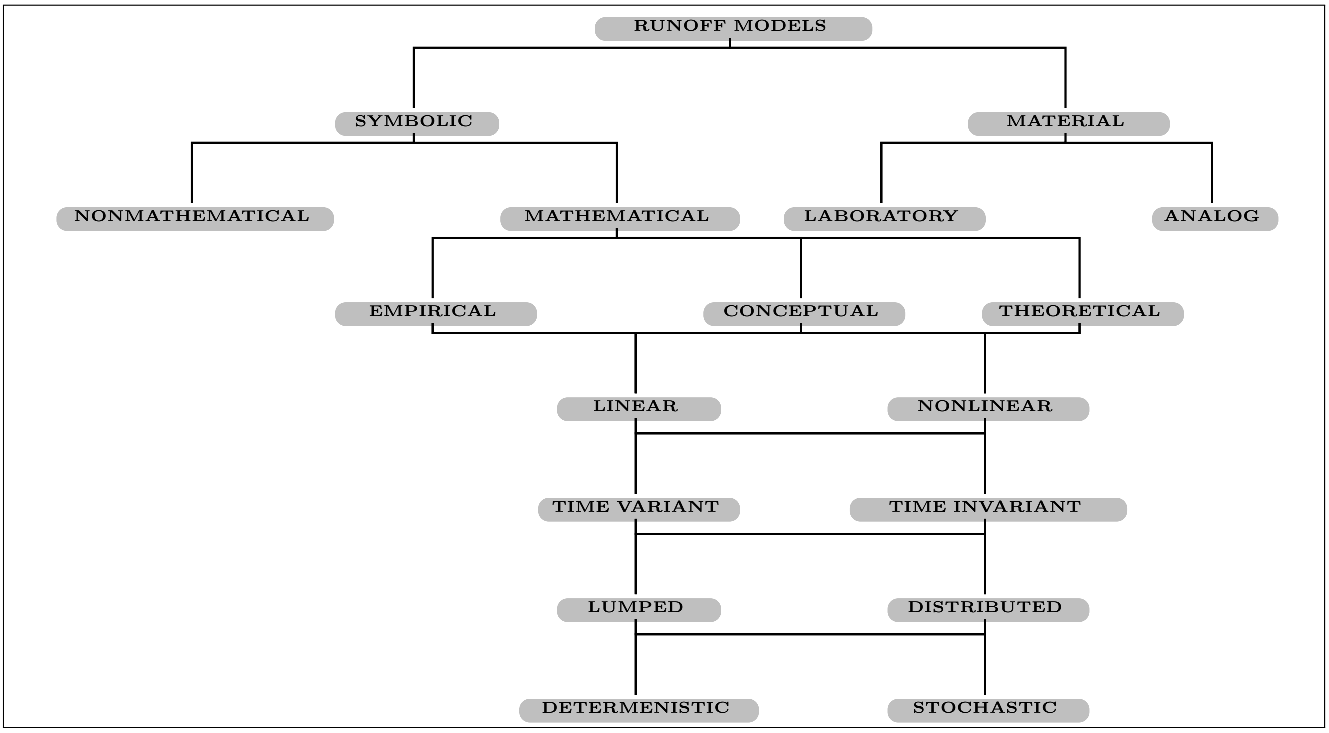

Figure 2.1: A classification of hydrologic models (Xu, 2002)

This thesis will focus on symbolic models and more specifically the stochastic component thereof, but more detail about the classification presented by Wilks (1998) will be provided in the next sections.

2.1.1.1 Symbolic Models

Symbolic models, also known as abstract models, represent the hydrological system in a mathematical form. The system and the way it operates is described by a series of equations that link the input and output variables. These variables can either be functions of time or space. The variables can also be random or probabilistic variables which do not possess a fixed value at a particular point in time and space, but instead are described by probability distributions. For example, the rainfall at a particular location in the future cannot be forecast exactly, but the probability that some rain will fall in future can be estimated (Chow et al., 1988). According to Vanmarcke (1983) the most general form in which such variables can be presented is a random field, a region of both time and space within which the value of a variable, at each point, is defined by a probability distribution. For example, the intensity of precipitation during a thunderstorm varies rapidly in time and location and can therefore not be predicted accurately; it is thus reasonable to represent it by a random field.

The development of a mathematical model containing random variables which are depended on both time and three space dimensions is nearly an impossible task and it is therefore necessary to simplify the model by limiting the sources of variation. In order to accomplish this simplification of a hydrologic model, Chow et al. (1988) presented three basic decisions that have to be made:

- Will the variables in the model be random?
- Will the variables be uniform in space or not?
- Will the variables be constant in time or not?

A visual representation of a hydrologic model is presented in Figure 2.2.

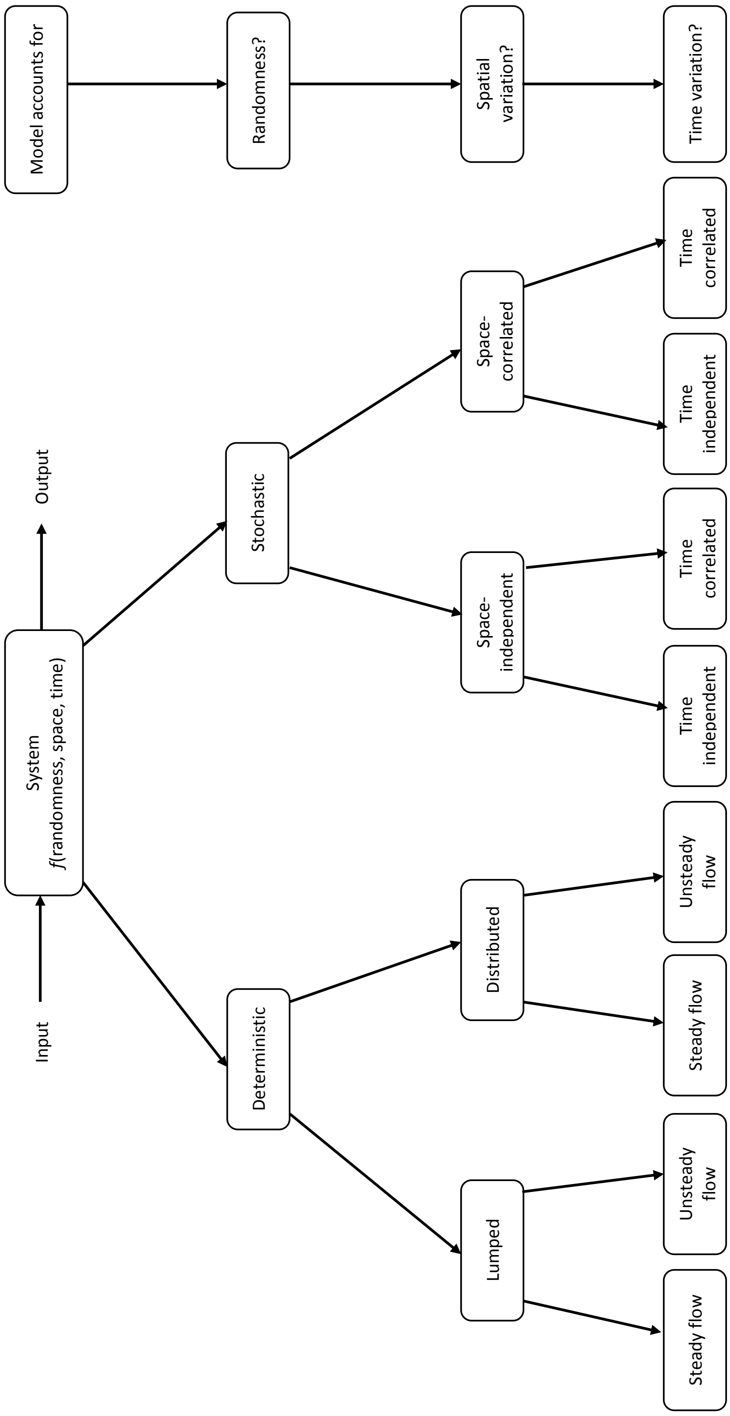

Figure 2.2: Classification of hydrologic models according to the way they treat the randomness and space and time variability of hydrologic phenomena (Chow et al., 1988)

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From Figure 2.2 it can be determined that randomness is not considered by deterministic models. For a deterministic model a given input will produce the same output. A stochastic model on the other hand has output that are in the very least partially random. According to Chow et al. (1988) deterministic models can be used to make forecasts while stochastic models can be used to make predictions. Randomness can however not be discarded completely from a hydrologic model. The variability in the output can, however, be insignificant when it is compared to the variability which result from known factors. In these cases it would be appropriate to use a deterministic model. In the case of large random variability, a stochastic model will be suitable, because output could vary vastly from a single value produced by a deterministic model. For example, with the use of vapour transport and energy supply data a reasonable good deterministic model of daily evaporation at a given location can be developed, but such data cannot be used to construct reliable models at the same location of daily precipitation as precipitation is largely random. Daily precipitation models are therefore of the stochastic nature.

Spatial variation is the another difference between stochastic and deterministic models to consider. Chow et al. (1988) stated that the hydrologic phenomena vary in all three space dimensions, but as previously mentioned it would compromise the practicality of the model if all these variations are accounted for. In the case of deterministic models the space variation is divided between lumped models, which are spatially average, and distributed models, which consider the hydrologic process that take place at various different points in space and thus define the variables in the model as functions of the space dimension. Stochastic models on the other hand are defined as space-correlated or space-independent according to whether the random variables influence each other at random points in space.

The third aspect to consider is the time variability. In the case of deterministic models time variation is divided into steady-flow (flow that does not change in time) and unsteady-flow models. In the case of stochastic models outputs will always vary in time. These models can be either time-correlated or time-independent; where a time-independent model represents a series of hydrologic events which do not influence each other, while time correlated models represent a series in which each event is partially influenced by the preceding one and possibly by other events in the series.

Chow et al. (1988) further conclude that all hydrologic models are representations of reality and thus the output of the actual system will never be forecast with certainty. As previously mentioned, the hydrologic phenomena vary in time and all three space dimensions, but for only a few idealised cases the simultaneous consideration of randomness, time, and three dimensions have been accomplished. Usually only one or two variation sources are considered in a practical model.

2.2 Mathematical Stochastic Modelling

One of the uses of stochastic hydrology is to determine and evaluate the reliability of the supply of a water resource system. The need for stochastic hydrology originated from the requirement to determine assurance of a water supply at, for example, a recurrence interval of a failure of 1:200 years. Streamflow data, in South Africa, that is recorded, rarely exceeds 40 years and data obtained through rainfall runoff simulation usually has a maximum period length of only 80 years. Stochastic hydrology provides a manner in which to synthetically increase the available data so that the behaviour of water resource systems can be evaluated using alternative, but statistically plausible, streamflow conditions. This provides the opportunity to evaluate the probability of occurrence of critical periods that can be up to nine years long, which is difficult given the relatively short historical time series (McKenzie et al., 2004).

As established in Section 2.1.1.1 stochastic models are random models consisting of spatial variables in all three dimensions as well as variables of time. According to Craigie et al. (1992) a stochastic process is a statistical process involving a number of random variables depending on a variable parameter, which usually is time. Lawrance et al. (1977) relate to this definition stating that if one observes a river, at a given point in time or space the natural flow is the primary function of the effect of rainfall during a previous period. The extent of this period and the function are dependent on the type of terrain, the water courses, the area of the terrain as well as the rates and areal distribution of rainfall input.

According to Haan (1977) any hydrologic system has to be designed to operate in the future. The generation of future watershed inputs in the form of, for example, solar radiation and precipitation, can not be done by means of deterministic models, as such models do not currently exist, nor is it likely that they will exist in the foreseeable future. It is thus necessary to make use of stochastic models to generate these inputs.

According to (Pegram et al., 2011) the main advantage of a stochastic model is that it can generate a large number of sequences, each with the same statistical characteristics, but not necessarily producing the same reservoir yield.

Stagge et al. (2013) stated that stochastic models originally used parametric disaggregation models that used statistical parameters from historical time-series to temporally disaggregate annual streamflows. In large hydrological systems, however, parametric models can have an unrealistic number of parameters. According to Prairie et al. (2007) recent advances in non-parametric hydrological modelling provide an attractive alternative to linear parametric models. Unlike the parametric model where a single linear model is fit to an entire data sequence, the non-parametric model contains a local functional fitting. The non-parametric aproach has the ability to capture any arbitrary features (for example: non-linearities and non-normalities) exhibited by the data. Lall (1995) provides a complete overview of non-parametric models.

2.2.1 The Use of Historical Records in Stochastic Models

When historical rainfall or streamflow data is the sole basis of a design, the stochastic streamflows would simply be the historical record itself. It should be noted that a historical record is only one realisation of a stochastic time series and that the historical record will be resembled in future realisations only in a statistical sense, even if the process is stationary. Over the years designers have discovered that for years the evaluations of their designs using historical or past records provide no guarantee that the design would perform satisfactorily in the future, as flow sequences in the future will not necessarily be the same as in the past (Haan, 1977). Haan further states that historical flow records are generally very short and in most cases cover less then 25 years; even if one is to look at a project with a flow record of 100 years, an observed sequence of 10 to 25 years will not repeat itself. It can therefore be established that the worst flood on record will, for example, not be the worst possible flood that may occur in the future.

A design based on historical records alone has a risk of inadequacy to it, because of the the unknown flow sequences that the system could experience.

2.2.2 Purely Random Stochastic Models

Purely random stochastic models are, according to Haan (1977) and Xu (2002), possibly the simplest stochastic model. In this model the events are assumed to occur at distinct times with the time between events being constant. The events at any given time are thus independent of the events at any other time, and the probability distribution of the event is known. Stochastic generation from a model of this type basically amounts to generating a sample of random observations from a single variable probability distribution. For example a random observation for any normal distribution can be represented with the relationship in Equation 2.1.

$$y = \sigma R_N + \mu \tag{2.1}$$

where $\mathrm{R_N}$ is considered a standard normal deviate, and σ (standard deviation) and μ (mean) are the parameters of the desired normal distribution of y.

2.2.3 Autoregressive Models

In statistics and signal processing, an autoregressive model is a representation of a type of random process. It describes certain time-varying processes in nature and economics. The autoregressive model specifies that the output variable depends linearly on its own previous values (Craigie et al., 1992). According to Salas (1980) autoregressive models have been used extensively for the modelling of annual and periodic hydrologic time series, since the early 1960s.

Whenever a standard normal distribution repeats itself, synthetic sequences cannot be constructed through a sequence of sample values from a probability distribution. If such a sequence is constructed, it will not take the relation between each number sequences and the number of preceding sequences into account (Xu, 2002). If one considers a second order stationary time series which is made up of a random as well as a deterministic part, the persistence effect is reflected by the deterministic part, whilst the random part is assumed to have a constant variance and a mean of zero. The autoregressive model is one which could be used to simulate such a series and the general form thereof is presented in Equation 2.2.

$$(y_t - \mu) = \beta_1(y_{t-1} - \mu) + \beta_2(y_{t-2} - \mu) + ... + \beta_k(y_{t-k} - \mu) + \epsilon_t \tag{2.2}$$

Where the mean of the series is represented by μ and, the regression coefficient by β, while $\{y_1, y_2, ..., y_t\}$ represents the observed sequence and ϵ_t is the random variable and is usually assumed to be independently and normally distributed with a mean of zero and a variance ${\sigma_\epsilon}^2$.

In hydrology the first order autogression presented in Equation 2.3 has become quite popular.

$$y_t - \mu = \beta_1(y_{t-1} - \mu) + \epsilon_t \tag{2.3}$$

This is also known as the first order Markov Model which was used to describe the frequency of wet and dry days. On days where rainfall were present, an exponential distribution was used to describe the amount of rain on that day (Bailey, 1990).

Autoregressive models are needed to generate synthetic annual data series for the purpose of planning and operating water resource systems and to generate synthetic periodic series for forecasting purposes. These models can also be used to generate synthetic time series of aggregated streamflows as well as for other operational problems, such as to generate synthetic time series at various sites in order to determine the reliability of dependable capacity of a hydroelectric system (Salas, 1980).

2.2.4 First Order Markov Process with Periodicity

The first order Markov process is a stochastic process and can be parameterised by estimating the transition probabilities empirically between different states in the observed systems. The process is one where each subsequent state depends only on the state immediately before it (Shamshad et al., 2005).

The first order Markov model presented in Section 2.2.3 assumes that the process remains stationary in the first three moments. This model can be generalised so that the periodicity in the hydrologic data is accounted for. According to Haan (1977) the generation of monthly streamflow was declared seasonality if the flows exists, is the main application of this generalisation. The model consists of twelve regression formulas in its simplest form.

The first order Markov process represents a system of elements that is moving from one state to another over time. According to Shamshad et al. (2005) many natural processes are considered as Markov processes. The Markov modelling approach has been used frequently for the generation of synthetic rainfall data. Srikanthan et al. (1985) and Thyer et al. (2000) used and recommended a first order Markov model to generate rainfall data. Thomas et al. (1962) first used a first order Markov model to generate streamflow data.

2.2.5 Moving Average Models

Moving Average models are flexible constructions, used to create a large number of autocovariance functions (Barry et al., 1996). According to Peterson et al. (2010) these functions are developed by creating random variables as the integration of Moving Average functions over a white noise random process.

The moving average model is one used frequently to smooth out various types of hydrologic time series including weekly, or daily air temperature, wind speed, evaporation rates. The the moving average process is somewhat different for generation of stochastic hydrologic data.

According to Raudkivi (1976) the moving average itself has not been successful in hydrological applications. If, however, the model is combined with the autoregressive model, which was discussed in Section 2.2.3, then it forms the Autoregressive Moving Average model (ARMA) that is capable of representing both stationary and certain non-stationary sequences.

2.2.6 ARMA

In Section 2.2.3 it has been established that autoregressive models have been used to successfully develop hydrologic time series. During flow recession, however, the flow at a particular time is said to be a fraction of the flow at a previous time interval. Recession can be represented using an autoregressive scheme. High flows are formed mainly through large rainfall or snow melts or both and the mixed behaviour can be modelled adding a moving average (MA) component (Section 2.2.5) to the autoregressive (AR) component to create an Autoregressive Moving Average model (ARMA). Flexibility is added to the model with combining of the MA and AR models and provides the possibility to build a model with the smallest possible number of variables. Variables are estimated from data and the idea of saving in the number of variables is very attractive (Salas, 1980).

ARMA models combine any direct auto-correlation properties of a data series. According to Todini (1988) the need for an ARMA model came from three requirements:

1. To extend the use of the model, obtaining longer continuous records which do no possess the complexity of base flow and storm runoff separation.

2. To use the model in complex watersheds with a large variety of slopes, soil, vegetation, etc.

3. To extend the model more or less without calibrating it with similar catchments.

One of the main advantages of the ARMA process is that it allows a model to be fitted with a relatively small amount of parameters, i.e. $p+q$. This amount of parameters would typically be smaller than the amount necessary for using an AR or MA model. This is called a parsimony of parameters and the first order of ARMA is presented in Equation 2.4.

$$x_t = \beta_1 x_{t-1} + e_t + \theta_1 e_{t-1} \qquad (-1 < \beta_1 < 1) \; and \; (-1 < \theta_1 < 1) \tag{2.4}$$

ARMA models are widely used in hydrology, econometrics, dendrochronology and other fields. Several reasons exist for fitting ARMA models to data. ARMA models contribute to the understanding of a physical system by revealing something about the physical process that builds persistence into a series. If one considers a simple physical water-balance model with precipitation as input for example, the model further possesses terms for infiltration, evaporation and groundwater storage. The model can be shown to yield a streamflow series as output that follows a particular form of the ARMA model. The model is also used to predict the behaviour of a time series from past values alone. These predictions can be used as a baseline to evaluate the importance of the other variables in the system (Meko, 2013).

2.2.7 Daily Data Generation Models

Even with the continued development of technology and data analysis systems, it is still a complicated process and problematic to generate synthetic series of daily events using certain types of data. The most difficult data to handle is considered to be daily processes such as streamflow, solar energy and temperature, because data from one day is dependent on data from the preceding day.

According to Xu (2002) streamflow is particularly difficult to model on a daily basis, because of the high level of persistence as a result of flood water drainage from the channel where it has been stored. The correlation during recession is considered to be very high for the flow of a given period. The magnitude of the auto-correlation can be a function of many different things, such as the size of the channel, the slope of the channel, the irregularity of the channel, the sediment content, the water temperature, and the condition and amount of vegetation on the channel banks. If these factors are changed, it will cause the auto-correlation coefficients to vary. Streamflow is further made up out of two components which possess entirely different characteristics. The first component is the surface runoff which is said to be a nonlinear response, as a result of the high level of control that evaporation, vegetation growth, soil moisture, and solar energy exercise on the flow characteristics. The second component is the groundwater flow which is said to be a more linear response, as it acts like drainage from reservoirs. The magnitude of these two components can vary quite considerably from one site or region to another.

Haan et al. (1982), O'Connell (1977), and Weiss (1977) have been known to make use of a shot-noise model to represent daily flow records as a stochastic process. The fitting of such models to daily hydrologic data is, however, considered to be a laborious and complex task.

2.2.8 Other Stochastic Models

There exist different stochastic models which are applicable to hydrology. Some of these models are, however, of such a nature that they cannot be classified into one of the previous categories.

Yevjevich (1972) suggested that a hydrologic time series may be modeled using a deterministic component and a stationary stochastic process. A deterministic component is composed of jumps, trends and periodicities, while the stochastic component consists of an auto-correlative type dependence and an independent stochastic component. The model reduces to a Markov model under certain conditions and has been applied to a number of hydrologic time series including ground water table level and water use time series (Law, 1974; Salas and Yevjevich, 1972).

A rainfall model is another example of stochastic models which is difficult to classify. Rainfall models will, however, not be described in detail in this document, but are available in Xu (2002).

2.3 Yield and Reliability of a Hydrological System

One of the main reasons for the simulation and analysis of a hydrological system is to determine whether the system would be able to handle various flow and abstraction situations and to calculate the reliability of the system.

2.3.1 Yield

The yield from a hydrological system is the controlled release from a reservoir system and is often expressed as a ratio of the mean annual inflow to the reservoir (McMahon et al., 2005). The ideal is that the yield of the system should be equal to the specified target draft (controlled abstraction from the reservoir over a specified time period), meaning that the system would be able to supply the required amount of water over the specified period of time. When the storage level of the system is low, however, depending on the operating policy, the yield may be reduced to less than the target draft. Thus, although it is desirable that the yield should be equal to the specified target draft, it may fall below the target draft in times of drought and may exceed the target draft in times where water is in abundance (Basson et al., 1994). The yield for a hydrological system can be divided into two parts, average yield and base yield.

The base yield of a hydrological system is the minimum annual withdrawal for a specific full storage capacity that can be sustained while attempting to satisfy a given target draft, using a particular inflow sequence. The base yield, therefore, represents the driest year in the analysis and is thus the minimum annual yield constructed monthly, for a monthly yield analysis.

The base yield is used to determine the historical firm yield of a hydrological system, with the historical firm yield being the amount of water that can be abstracted from the system while not exceeding the amount of water available in the system at any given time. The historical firm yield, therefore, is the maximum base yield that can be abstracted from the system for a given inflow sequence.

The average yield of a hydrological system is the average of the sum of total volumes yielded annually by the system that was cumulatively constructed over a specified time period (daily, weekly, monthly).

An example of the average yield, base yield and historical firm yield of a hydrological system are graphically presented in Figure 2.3.

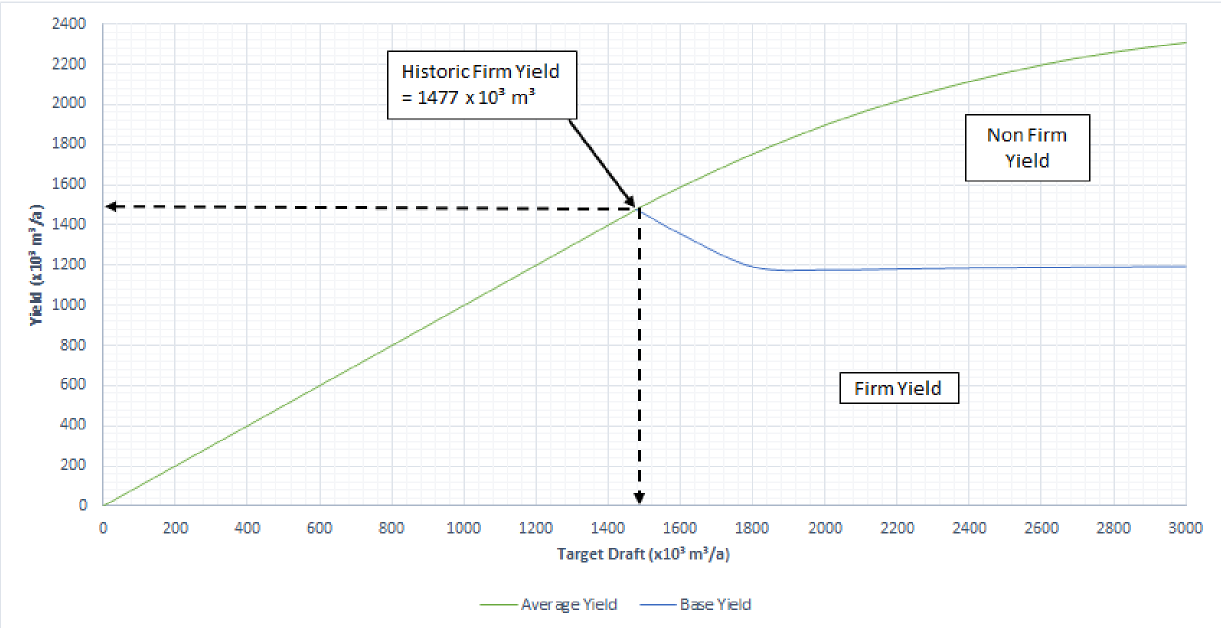

Figure 2.3: Example of the average yield, base yield and historical firm yield of a hydrological system

2.3.2 Reliablity of Supply

With the construction of a yield analysis of a hydrological system, it is possible to determine how reliable the system is and if the system would be able to provide a certain amount of water over a specified time period. In order to determine the reliability of a system, the risk that the system could fail has to be calculated.

Basson et al. (1994) define the risk of failure of a hydrological system as the probability of the system not being able to supply the base yield associated with a specific target draft at least once over a specified time horizon. The reliability of supply of the system can be defined as the probability of the system being able to supply the base yield associated with a specific target draft without failure over a specified time horizon.

According to Basson et al. (1994) it is common practice to make use of the recurrence interval concept to quantify risk of failure of a reservoir in a hydrological system. The recurrence interval of failures is the average time between the occurrence of failure events. Recurrence intervals associated with large reservoirs are typically 1:20, 1:50, 1:100 and 1:200 years. The probability of a reservoir failing in a particular year (annual risk of failure) is the reciprocal of the recurrence interval. Therefore a probability of 2% in any one year is equivalent to a recurrence interval of 50 years, which can be calculated with Equation 2.5.

$$R = \frac{1}{T} \tag{2.5}$$

Where:

R = Annual risk of failure.
T = Recurrence interval of failures.

The probability of a reservoir successfully meeting the water demand in a particular year (annual reliability of supply) is simply one minus the annual risk of failure. Annual reliability is therefore related to the recurrence interval of failure by the relationship presented in Equation 2.6.

$$E = 1 - \frac{1}{T} \tag{2.6}$$

Where:

E = Annual reliability of supply.

The long-term risk of failure is related to the annual risk of failure by the well-known Bernoulli probability relationship presented in Equation 2.7.

$$\begin{aligned} R_n &= 1 - (1 - R)^n \\ &= 1 - (1 - \frac{1}{T})^n \end{aligned} \tag{2.7}$$

R_n = Long-term risk of failure
n = Planning period in years

The long-term reliability of supply is simply one minus the long-term risk of failure and is presented in Equation 2.8.

$$E_p = (1 - R_n) \tag{2.8}$$

Where:

E_p = Long-term reliability of supply

A relationship between the long-term reliability of supply and the recurrence interval of failure can be established and is presented in Equation 2.9.

$$RI = \frac{1}{1 - E_p{}^{\frac{1}{n}}} \tag{2.9}$$

2.4 Stochastic Generators

Stochastic weather and streamflow generators are used in a wide range of studies, such as agricultural risk assessments, environmental management and hydrological applications (Semenov et al., 1998). These generators are used to generate synthetic sequences of weather and streamflow variables which are statistically consistent with characteristics of the observed historical record. These sequences are commonly used for risk and reliability assessment in the operation and design of agricultural and water resource systems (Mehrotra et al., 2006). Fodor et al. (2013) relate to this stating that stochastic weather and streamflow generators produce artificial data series which can be used in a wide range of hydrological, agro-meteorological, climate change and risk analysis studies. According to Richardson (1981) and Richardson and Wright (1984) a stochastic weather or streamflow generator is a numerical model that produces synthetic sequences of climate or streamflow variables such as temperature, solar radiation and precipitation with certain statistical properties.

According to Semenov et al. (1998) several reasons exist for the development of stochastic weather and streamflow generators and for the use of synthetically generated weather and streamflow data instead of observed data. The first reason is that stochastic generators provide weather and streamflow time series long enough to be used in risk assessment in agricultural and hydrological applications. Another reason is that it provides a means in which the simulation of weather and streamflow can be extended to locations where observed weather and streamflow data is not available. Figure 2.4 provides a schematic layout of the stochastic generation process, using an AR(1) model build from the historical time series.

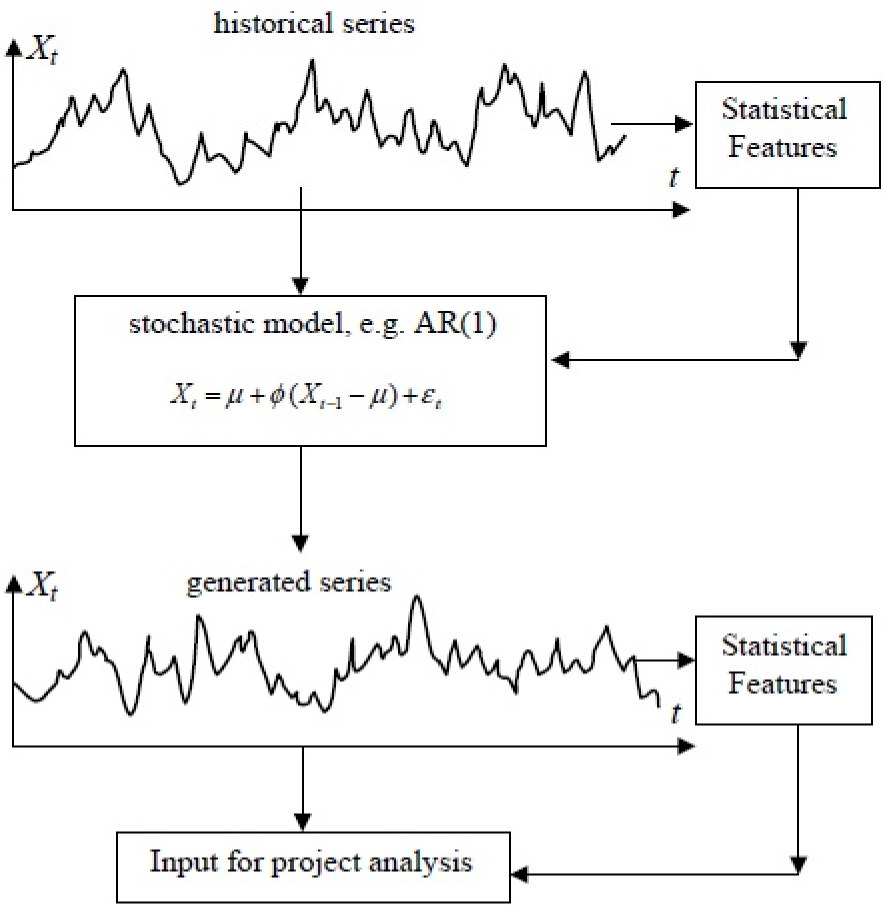

Figure 2.4: Schematic of stochastic generation using an AR(1) model, built from the historical series (Sveinsson et al., 2003)

Different stochastic streamflow generation software packages exist all around the world. A few of these packages will be discussed in the sections to follow.

2.5 STOMSA

The Stochastic Model of South Africa (STOMSA) is a monthly multi-site stochastic streamflow model which provides direct input to the WRYM and is used when analyses are undertaken that require stochastically generated streamflow sequences. These sequences are generated internally when the WRYM program is executed. STOMSA can also be used separately from the WRYM to generate stochastic streamflow sequences.

2.5.1 Development of the Model

STOMSA was developed in the early 1980s for the then Department of Water Affairs and Forestry (now the Department of Water and Sanitation) by Professor GGS Pegram according to McKenzie et al. (2004) and Pegram (1986) as part of the Vaal River System Analysis Study. The primary objective of the model was to serve as a generic streamflow generator that is technically sound and versatile in nature so that it can be incorporated with the models used to analyse the water resource systems of South Africa.

The stochastic streamflow generation techniques contained in STOMSA are based on an annual time step with a monthly separation feature. Even though the model is considered to be appropriate for a variety of hydrological conditions in South Africa, careful consideration should be taken in cases where the critical period of a water resource system is shorter than a year. In these cases a stochastic model based on monthly flows could be required instead of annual flows.

2.5.1.1 Stochastic Streamflow Generation Process

According to McKenzie et al. (2004) the generation of sound stochastic streamflow sequences is based on acceptable historical naturalised streamflow data that was derived by means of thorough hydrological assessments. The process begins with the capturing of all the various statistical properties contained in the historical streamflow sequence of each incremental sub-catchment under investigation. The various statistical properties are captured by identifying the appropriate statistical distribution models and parameter sets which best describe the following:

- The marginal distribution characteristics of the annual flows. The purpose is to identify a distribution that can transform annual flows to a normal distribution the best.
- The time-series distribution which represents the serial correlation, that is exhibited by the normalised annual flows, the best. The normalised residual annual flows are then determined using the results.
- The cross-correlation between the normalised residual annual flows from multiple catchments.

The annual stochastic flow values for a particular sub-catchment are generated, based on the selected statistical distribution models and parameter sets, by following the same steps as for parameter estimation above, but are applied in reverse order. The process begins with random number generation and is then followed by cross-correlation and serial correlation characteristics and then finally the marginal distribution model is applied. The generation of monthly stochastic flows is based on the annual stochastic flows which are separated into 12 corresponding monthly values.

2.5.1.2 Marginal Distribution

According to Hoffman et al. (2015) and McKenzie et al. (2004) the marginal distribution of a streamflow sequence is all the annual streamflow values plotted against probability of exceedance. This means that all the annual streamflows are ranked according to their magnitude from small to large. Each value is then assigned a rank and plotted against the rank divided by the total number of streamflow values. The marginal distribution can also be presented in terms of standard deviations from the mean. A distribution is chosen which best fits the data. It should be noted when choosing a distribution, that low-flow sequences affect the reliability of the system the most.

When STOMSA selects a marginal distribution, it either uses a log-normal distribution or a bounded distribution. The selection of distribution is based on various statistical criteria which are described by the Hill Algorithm that is based on the Johnson Transform Suite (Hill et al., 1976). The log-normal distribution is presented in Equation 2.10 and the bounded distribution is presented in Equation 2.11.

$$y = \gamma + \delta \; ln(x - \xi) \tag{2.10}$$

$$y = \gamma + \frac{\delta \; ln(x - \xi)}{\lambda + x - \xi} \tag{2.11}$$

Where:

x is an annual streamflow variant;
y is the transformed variant;
$\xi < x < \lambda$;
γ(Gamma), δ(Delta), ξ(Xi) and λ(Lambda) are parameters.

2.5.1.3 Serial Correlation

According to Hoffman et al. (2015) a serial correlation of a time series is the analysis of the Markovian relationship of the time series. According to McKenzie et al. (2004) the sequence of normalised annual historical streamflows can be analysed using one of nine ARMA(ϕ, θ) model types (Section 2.2.6), where ϕ refers to the auto-regressive parameters and θ refers to the moving average parameters. The most appropriate ARMA model type is selected by STOMSA based on a selection criteria from ARMA(0,0), ARMA(0,1), ARMA(0,2), ARMA(1,0), ARMA(2,0), ARMA(1,1), ARMA(1,2), ARMA(2,1), ARMA(2,2).

Once STOMSA has selected the appropriate time-series model, it is applied to the normalised historical streamflow data in order to “remove” its serial correlation characteristics. This results in a corresponding set of normalised residual annual historical streamflows.

2.5.1.4 Cross-Correlation

When stochastic streamflow data is generated for two or more sub-catchments simultaneously, then the inherent inter-dependence between the flows which occur within the catchments must be preserved. The preservation of the inter-dependence between the flows is required for the generation of sequences that exhibit correlating properties similar to those of the adjacent catchment and is particularly important for the yield analysis of water resource systems with inter-basin transfers.

The normalised residual annual historical streamflows is the basis from which the cross-correlation, which occurs between flows from multiple catchments, is determined. The cross-correlation is determined using a technique called Singular Value Decomposition. The result is a set of matrices which is used to re-generate the cross-correlation dependencies among all the runoff sequences that are considered for a weather resource system. The matrix parameters along with the marginal distribution results and serial correlation analyses are written to a stochastic parameter file which is generally referred to as the PARAM.DAT file. The parameter file, together with sophisticated computational routines, is used in the generation of stochastic streamflows (McKenzie et al., 2004).

2.5.1.5 PARAM.DAT File

The PARAM.DAT file is created by a program called CRSMK6. The file contains information on the estimated marginal distribution of the annual flows as well as the parameters of the transformation of the annual flows to normalised variates. CRSMK6 takes the fitted ARMA(ϕ, θ) model parameters ($\phi, \theta = 0$, 1 or 2) as well as the white noise residuals and computes the interdependence between the annual flow residuals from the various flow stations. The calculation is done under the assumption of normality of the residuals so that the cross-covariance matrix is the measure of the extent of the interdependence of the residuals. The cross-covariance matrix is then decomposed into its square root, using a technique called singular value decomposition.

The PARAM.DAT file therefore contains all the information relevant to generating properly cross-correlated annual flow sequences with the correct serial dependence structure (DWA, 2010).

2.5.1.6 Monthly Disaggregation

During the early nineteen eighties, when the development of stochastic models was in progress, various approaches for the generation of monthly flow values were considered. The final approach which was adopted is based on a technique where each annual stochastic flow gets separated (disaggregated) into 12 corresponding monthly values. It was found that the disaggregation method produced realistic monthly values without the need to develop a complex monthly stochastic flow generator.

McKenzie et al. (2004) describe the process of disaggregating annual flows into monthly flows, stating that it is undertaken based on a user defined set of so-called key gauges. If 40 sub-catchments are included in the streamflow generation process, for example, then 10 of these sub-catchments might be considered to be the most important and will thus be selected as the key gauges. The generated stochastic annual flows for each key gauge are compared with the historical time series to identify the year where the total flow is the closest to the generated annual flow value. If there are 10 key gauges, then 10 such years will be identified. In some cases the same year could be identified multiple times, the year 1950 could, for example be selected for five of the 10 gauges. It is, however, not unusual to have 10 different years. After the 10 key years are identified, a simple least square fit-analysis is done between the stochastic value and historical value of all the catchments. The year in which the stochastic and historical values fit all the catchments the best, is then used in the monthly distribution.

If, for example, 1950 is selected, then the distribution for 1950 in catchment A is used to disaggregate the annual flows in catchment A, while the 1950 distribution in catchment B is used to disaggregate the annual flows in catchment B. This process is followed for all the catchments and all the stochastic values in the series.

2.5.1.7 Verification and Validation

When stochastic streamflow generation is undertaken, the primary objective is to develop a realistic alternative sequence of flow data which can be used for the determination of the assurance of a supply from a water resource system. It is important to note that for the validity of the stochastic streamflow sequence a careful assessment is required in order to ensure that the yield results are in fact realistic, reliable and plausible.

STOMSA uses two two different classes of tests to check the stochastically generated data:

- *Verification tests* are used to re-sample various statistics from generated sequences to ensure the reproduction of statistics from the historical sequence within reasonable boundaries. For example the mean and standard deviation of a stochastic sequence are compared with that of the historical sequence.

- *Validation tests* involve the testing of certain features of the sequences that were generated and not directly employed as part of the generation process. All the tests which are conducted in this category relate to the role of reservoir storage and include the maximum deficit, duration of maximum deficit, duration of longest depletion and yield-capacity relationship tests. It should be noted that these tests are always undertaken while assuming there is zero evaporation losses from the reservoir water surface.

Both these tests are undertaken through the generation of a number of stochastic streamflow sequences and then calculating the value of the characteristic under consideration for each sequence. This results in a range of values that is put forth as a distribution by means of a box-and-whisker plot, as seen in Figure 2.5. The plot is evaluated by comparing it to the corresponding value from the historical data. These results are taken as acceptable when the historical value is between the 25 and 75 percentiles.

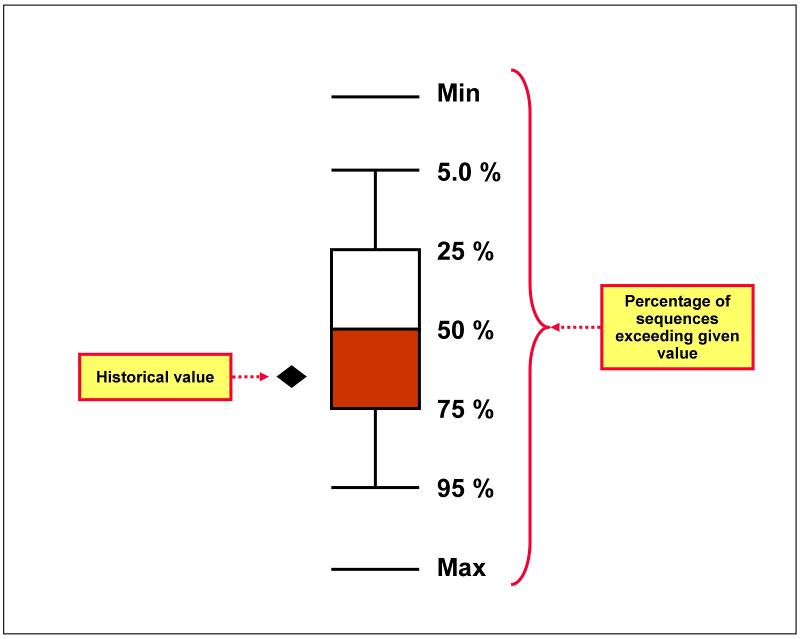

Figure 2.5: Typical definition of a box-and-whisker plot (McKenzie et al., 2004)

When the historical value falls outside the normally accepted limits, the analyst has to decide if there is a problem with the historical naturalised data or perhaps if there is a shortcoming in the stochastic model. It should be considered that no stochastic model is perfect, especially a stochastic model where stochastic sequences are generated simultaneously for multiple catchments. Errors and anomalies should be evaluated individually to ensure that they are small enough not to possess a significant influence on the overall result of the analysis. This model is said to be one of the most robust available and has been thoroughly tested over the years. The model is, however, not necessarily applicable to every water resource system and in certain cases some modifications may be required (McKenzie et al., 2004).

2.5.2 Basic Structure of the Model

STOMSA is a user-friendly application used to preform the flow generation, parameter estimation, verification and validation tests which form part of the stochastic streamflow generation process. The model functions using a Windows operating system and makes use of existing DOS-based routines coded in Fortran.

The model further contains a Graphical User Interface (GUI) that was coded in Delphi. The GUI provides a manner for the user to manage the operation of the model, including the input of data and extraction of results, using standard Windows-type control features. The GUI is divided into two components namely the main model control window, which provides the user with access to the model controls, and a window that is used to display the graphical results.

The basic approach in the development of STOMSA was to provide the user with the facility to input information into the model as well as receiving results from the model (McKenzie et al., 2004).

2.5.3 Model Data Requirements

As previously mentioned the generation of stochastic streamflow data involves the estimation of statistical modal parameters that are based on the sequences of historically observed natural streamflow data. These sequences can be obtained through simulation, by means of rainfall-runoff modelling, or by the naturalisation of actual recorded flows. Recorded flows are naturalised taking all the factors that affect flow in the sub-catchment into account and then adding the impact of those back into the recorded flows. This results in a set of flows that would have occurred historically if there had not been any developments inside the catchment area (McKenzie et al., 2004).

Natural historical streamflow data, in the form of monthly time-series data files, is used as input to STOMSA. The analysis considers one monthly time-series data file for each of the sub-catchments and it is therefore important to take note of the following:

- All files must be in the *HRU standard flow file format*, with data in hydrological years (normally starting in October for South African conditions) and the units of million m^3.
- All the files must be named with the $*$.INC file-extension. This is a convention that is followed to show that incremental runoff is represented. If the Bloemhof Dam is analysed for example, then the corresponding data file might be called *BLOEM.INC*.
- The record period does not have to be the same for all the various data files used in a given analysis.
- All the files do not have to be in a single directory. Each file can have an individual location which is specified by the user via a standard file navigation dialog.

2.6 SAMS

The Stochastic Analysis, Modelling and Simulation model, better known as SAMS, is a software package used for the stochastic analysis, modelling and simulation of hydroligic time series such as streamflows. SAMS has been developed in collaboration between the Colorado State University and the U.S. Bureau of Reclamation, and was originally written in MS Visual C++ and Fortan. SAMS is capable of analysing single site as well as multisite annual and seasonal data. Seasonal analyses can include anything from half-yearly up to weekly stochastic streamflow generation (Sveinsson et al., 2003).

2.6.1 Capabilities of SAMS

SAMS was first released in 1996, namely SAMS-96.1, but over the years the model has undergone a number of modifications and corrections. According to Sveinsson et al. (2007) the most recent version of SAMS is the SAMS 2007. This model includes new data analysis features and modelling approaches and has the following capabilities:

- Analysis of the stochastic features of annual and seasonal data.
- It includes several types of transformation options to transform the original data into a normalised distribution.
- It includes a number of single site, multisite, and disaggregation stochastic models that have been widely used in hydrologic literature.
- It includes two major modelling schemes for data generation of complex river network systems.
- The number of samples that can be generated is unlimited.
- The number of years that can be generated is unlimited.

Sveinsson et al. (2007) further state that the main purpose of SAMS is to generate synthetic hydrologic data so that a stochastic simulation of hydrologic time series, such as annual and monthly streamflows, can be developed.

2.6.2 Primary Features of SAMS

According to Sveinsson et al. (2003) and Sveinsson et al. (2007) SAMS consists of three primary applications namely:

- The analysis of stochastic data.
- The fitting of a stochastic model.
- The generation of a synthetic series.

These applications with their main features are summarised in Table 2.1.

Table 2.1: Main features of SAMS 2007 (Sveinsson et al., 2007)

Main Fuctions	Temporal Scale	Features
Stochastic Analysis	Annual	Basic 1st and 2nd order statistics and skewness
		Drought related statistics
		Surplus related statistics
		Storage related statistics
		Data transformation
	Seasonal	Same as above
	Sub-seasonal (e.g. weekly)	Same as above
	Daily	Same as above
Stochastic Modelling	Annual	Single site: AR(p), ARMA(p,q), GAR(1), SM
		Multisite: MAR, CARMA, CSM, CSM-CARMA
		Spatial disaggregation: VS, MR
	Seasonal	Single site: PAR(p), PARMA(p,q)
		Multisite: MPAR(p)
		Scheme 1:
		Univariate generation, annual at index-station
		Spatial disaggregation, annual at index station to annual at key station
		Multivariate disaggregation, annual at key stations to annual at substations
		Multivariate disaggregation, annual at substations to annual at further upstream stations ect.
		Multivariate disaggregation of annual to seasonal at any group of stations
		Scheme 2:
		Multivariate generation, annual at key stations
		Then the same steps as above
		Scheme 3: (Grygier-Stedinger's method)
		Multivariate generation, annual key stations
		Multivariate disaggregation, annual to seasonal at key stations
		Multivariate spatial disaggregation, seasonal at key stations to seasonal at substations
		Multivariate spatial disaggregation, seasonal at substations to further upstream stations
	Sub-seasonal (e.g. weekly)	Not currently available except in one step
	Daily	Not currently available
Stochastic Simulation	Annual	Available for any models/schemes as specified above
	Sub-seasonal (e.g. weekly)	Not currently available
	Daily	Not currently available

2.6.2.1 Analysis of Stochastic Data

The analysis of stochastic data is one of the main applications of SAMS. This application has a number of functions such as data plotting, confirming the normality of data, the transformation of data, and the computing and displaying of the statistical or stochastic characteristics of the data.

Data plotting helps with detecting outliers, trends, shifts or errors in the data. The application further includes probability plots in order to verify the normality of the data. The data can also be transformed into normal data with the use of various transformation techniques, such as logarithm, gamma, and power transformations.

SAMS is able to calculate a number of statistical characteristics. These characteristics include the basic statistics such as the mean, skewness, standard deviation, spectrum, serial correlations, season-to-season correlations, both serial and season-to-season correlations (for multisite data), as well as surplus, drought and storage related statistics. These statistics are used to confirm the normality of the generated stochastic data.

2.6.2.2 Fitting of a Stochastic Model

The second application of SAMS is the fitting of a stochastic model. This application includes parameter estimation and model testing for alternative as well as multivariate models. These processes make use of a number of models which are summarised in Table 2.1.

For stochastic simulations at several sites in a hydrologic network, the application provides a direct modelling approach that is based on multivariate autoregressive and ARMA processes which are available for annual data, and a multivariate periodic autoregressive process which is available for seasonal data. A key concept of the application in SAMS is that of temporal and spatial disaggregation. SAMS is able to handle an unlimited sequence of flow stations.

SAMS has three schemes available for modelling data of key as well as upstream stations. These schemes are summarised in Table 2.1. In Schemes 1 and 2 annual streamflow generation is conducted first and thereafter the annual quantities are temporarily disaggregated into seasonal. In Scheme 3 the annual quantities are also the first to be generated at the key stations, after which they are spatially disaggregated into seasonal quantities at the other upstream stations. Whenever seasonal data (e.g. monthly) is desired in either Schemes 1 or 2, temporal disaggregation models are fitted to disaggregate the annual values at desired stations into seasonal values.

It should, however, be noted that even though seasonal time scales can be any period from monthly, quarter-monthly, weekly, or any desired partition form of the calender year; the current disaggregation models are not recommended for time periods shorter than a week.

2.6.2.3 Generation of a Synthetic Series

The third primary application of SAMS is to generate stochastic streamflow series, in other words simulating synthetic data. This data generation is based on all the models, approaches and schemes described in Table 2.1. The model parameters used for the purpose of data generation are the parameters estimated by SAMS. According to Sveinsson et al. (2007) SAMS also allows the user to import annual series at key stations which were generated using software other than SAMS.

Sveinsson et al. (2007) further state that the statistical characteristics of the generated data are represented in tabular as well as graphical forms along with the historical statistics of the data used in fitting the generated model.

The overall data generation procedure based on Scheme 2 is summarised as follows:

1. A multivariate model, such as AR(p), is utilised to generate flows at key stations.
2. A spatial disaggregation model is then used to disaggregate the generated annual flows at the key stations into annual flows at the substations, followed by additional spatial disaggregation until all upstream stations are taken into account.
3. Finally a temporal disaggregation model is used to disaggregate the annual flows at one or more groups of stations into corresponding seasonal flows at those stations.

2.6.3 Applications of SAMS

According to Sveinsson et al. (2014) SAMS has been applied or used for a number of purposes over the years. SAMS has been used in the following applications:

- Modelling of the Upper Colorado River flows for the CRDSS project Ayres Associates, 1999.
- Statistical analysis of the Snake River streamflows W.L. Lane for Simons and Associates, 2000.
- Stochastic analysis and modelling of hydrologic time series Short course at the National Agriculture University, La Molina, Peru, 2000.
- Workshop on Stochastic Analysis Modelling and Simulation Colorado State University and U.S. Bureau of Reclamation, 2001.
- Analysis and simulation of the Great Lakes net basin supplies U.S. Canada International Joint Commission, HydroQuebec, and GLERL-NOAA, 2001-2004.
- SAMS was successfully applied to developing stochastically generated streamflow data sets for implicit stochastic optimisation of reservoir operations in the Geum River Basin, South Korea. Colorado State University and the Korea Water Resources Corporation, 2004-2005.
- Stochastic generation of the monthly flows of the Truckee River system Colorado State University and U.S. Bureau of Reclamation, 2005.
- Stochastic simulation of the Colorado River System streamflows Colorado State University and U.S. Bureau of Reclamation, 2006.
- International Course on Stochastic Hydrology National Agriculture University, La Molina, Peru, 2008.

- Stochastic forecasting models Master of Advanced Studies in Water Resources Management and Engineering, ETH, Zurich, Switzerland, 2008.

The list of applications provide an indication of the general areas or countries where SAMS has been used in the past.

2.7 Water Resource Yield Model

The Water Resource Yield Model (WRYM), as part of other water resources systems models, was developed by BKS (Pty) Ltd in conjunction with the South African Department of Water Affairs and Forestry (now the Department of Water and Sanitation) in the 1980s. The WRYM is a highly modified version of the original Canadian ACRES model for which the Fortran source code was obtained. The ACRES model was written and developed at ACRES by RB Allen and more information on the ACRES model is available in ACRES (1986).

The WRYM is a network-based water resources model used to analyse complex water systems under various operating and growth scenarios. A few years later the Water Resource Yield Model Information Management System (WRYM IMS) was developed. The WRYM IMS is a user interface for the WRYM that serves to improve data management and output viewing facilities to increase model use efficiency and decreases the set-up time and costs. The interface also provides users with expanded possibilities with data access and sharing (Logicon, 2010).

The latest version of the WRYM is incorporated within the Water Resource Modelling Framework (WRMF). The WRMF is a user friendly framework that acts as a data management system for the yield model. The framework includes data visualisers in order to view the data intelligently.

2.7.1 Development of the WRYM

Although many of the functions and procedures in the WRYM are still the same as those in the ACRES model, RB Allen made considerable modifications to the model. One very important addition to the acres model was made to enable the model to analyse not only historical data sequences but also numerous stochastic flow sequences. The stochastic capabilities of the model were designed by Pegram (1986) and make the current version of the WRYM one of the most sophisticated hydrological simulation models in use today (McKenzie et al., 1999).

According to Haumann et al. (2006) the WRYM was developed based on the assumption that a water resource system can be represented using nodes and links with the primary input to the model being the natural flows. The model allocates the various losses and demands in the system and generates monthly “present day” flow. The allocation of specific demands in the system is achieved through the assignment of penalties, where the highest penalty demand receives first priority in the allocation of supply.

Haumann et al. (2006) further state that the WRYM has a variety of uses and it is therefore required that the model is able to calculate various different variables and time series.

The model takes account of:

- monthly natural flows at nodes;
- diffuse irrigation and afforestation;
- precipitation at and evaporation from reservoirs;
- specific demands (domestic, agriculture and industry);
- losses in channels.

The model generates monthly time series data of:

- stream flow for each requested channel;
- reservoir level;
- reservoir volume;
- yield of the entire system or subsystem;
- assurance level for various target demands.

According to McKenzie et al. (1999) the WRYM relies on a network solver to optimise the water allocation in a river system. This solver is based on a set of penalties for channels, storage and demands at various nodes and links. The solver further minimises a cost function that is based on allocation and storage deficit cost, but also between different forms of storage within a catchment. The model makes use of a penalty structure at its core in the decision making about the location or storing of water within the system. These penalties are assigned to link supplying reservoirs and other water sources to users. The penalties (or value in this case) are further used to distinguish between different forms of storage in reservoir nodes across the catchment (Juizo et al., 2008).

2.7.2 Historical Yield Analysis

The WRYM is able to determine the historical firm yield of a hydrological system. The WRYM requires two annual target drafts to be specified. The one target draft must be small and the system must be able to supply the water requirements, while the second target draft has to be large and the system must not be able to supply the required amount of water. The WRYM makes use of an iterative process between the two specified target drafts until it finds the historical firm yield (*WRMF Manual* 2010).

2.7.3 Stochastic Streamflow Generation and Analysis

One of the most significant features of the WRYM is its ability to generate and analyse stochastic streamflows. According to McKenzie et al. (1999) the use of stochastically generated streamflow sequences is a standard practice in South Africa and the same techniques have been used successfully in several other parts of the world. The WRYM makes use of STOMSA (Section 2.5) as an internal stochastic streamflow generator.

When a stochastic yield analysis is undertaken in the WRYM, the user is allowed to choose the number of stochastic streamflow sequences to be generated and analysed. The *WRMF Manual* (2010) recommends that 201 stochastic streamflow sequences are generated for a long-term stochastic yield analysis and 501 stochastic streamflow sequences for a short-term stochastic yield analysis.

The WRYM uses these generated sequences to assess the reliability characteristics of a hydrological system. The WRYM calculates the long-term risk of failure, long-term reliability of supply and recurrence interval of failures by means of Equations 2.12, 2.13, 2.14.

Long-term risk of failure:

$$R_n = \frac{Failure\ Sequences + 1}{Total\ Sequences} \tag{2.12}$$

Long-term reliability of supply:

$$E_p = 1 - R_n \tag{2.13}$$

Recurrence interval of failures:

$$RI = \frac{1}{1 - {E_p}^{\frac{1}{n}}} \tag{2.14}$$

Where:

R_n = Long-term risk of failure
E_p = Long-term reliability of supply
RI = Recurrence interval of failures (years)
n = Number of years in the analysis.

2.7.4 Output File

The WRYM is able to process many different output files that contain various different results and information regarding the yield analyses of a hydrological system. The output file that is used the most for yield analyses by the WRYM and contains the most important results is the SUM.OUT output file.

The SUM.OUT output file is generated for all model runs and is the main data output file for the WRYM. The file contains month-end reservoir information, average monthly channel flows and analysis summary information for the system (*WRMF Manual* 2010).

2.7.5 The use of the WRYM

The WRYM has been used extensively since 1985 for the optimisation and system yield analyses of reservoirs in South Africa. The usual approach of the WRYM for large reservoir systems is to subdivide the system into subsystems which possess characteristics that are more understandable. The model further uses a 'balanced system' concept that enables the system of several reservoirs to be handled as a single reservoir subjected to a target draft. This target draft, which will satisfy multiple reliability constraints, can be obtained using the long term yield characteristics. The WRYM, however, does not supply a method to ensure that the reliability constraints for a specific demand obtaining water from a specific reservoir will be met (Ndiritu, 2006).

2.7.6 Comparison with other Models

Juizo et al. (2008) compared three water system analysis models namely the WRYM, the Water Evaluation and Planning system (WEAP21) and the Water Allocation Flow Model in Excel (WAFLEX) and presented the results listed in Table 2.2.

Table 2.2: Configuration used for three system models applied for Umbeluzi river basin (Juizo et al., 2008)

Model	Allocation methodology	Optimisation methodology	User friendliness	Transparency
WRYM	Minimises system penalty based on penalties per unit water set for failing to meet minimum flow requirements or demands. Higher penalties are given for failing to meet prioritised water use. Different penalties for same user type can be given.	A numerical routine is to the run optimisation for each time step.	Software available at DWAF, South Africa. Difficult to use without thorough training.	Because of the complex penalty structures and system optimisation routine transparency is limited.
WAFLEX	Releases from reservoirs are reduced according to storage rates. When released, as a base rule: first comes, first served. However, possibilities to include routines to prioritise types of water uses.	No optimisation	Uses EXCEL spreadsheets. Lecture notes on the development of models are available from IHE-Delft. Easy to use.	For basic use the spreadsheet methodology makes it transparent. However for non skilled users, if special Macro functions are applied it limits transparency.
WEAP21	Priorities are set for which reservoirs to draw water from. Amount of water for releases is reduced depending on storage situation allowing for rationing in times of deficit. When released allocations downstream is made according to given priorities for each type of water use. For equal priorities upstream users are provided first.	No optimisation	GIS based interface which gives good overview of the river system. Software available from SEI web page. Easy to use.	Fairly transparent through its GIS interface and straight forward priority system.

According to Juizo et al. (2008) the WRYM is a flexible model in the manner which it handles water allocations to different users in a catchment. The numerical optimisation, however, is limited to the downstream users of each reservoir. Fortunately in the case where there exist complex interconnections of reservoirs in the basin, these connections can be incorporated in the model and, according to Juizo et al. (2008), studies have shown that the WRYM is the preferred tool for system analysis of international river basins.

2.8 MIKE Hydro Basin

Mike Hydro Basin is a physical and conceptual model system for catchments, rivers and flood plains. The MIKE Hydro model is one of the systems that forms part of the MIKE Zero modelling framework developed by the Danish Hydraulic Institute (DHI) (DHI, 2013). According to the (DHI, 2014), MIKE Hydro offers a good map-centric user interface for intuitive model building, parameter definition and results presentation for water related applications.

2.8.1 General Operation

Previously MIKE Basin was presented as an extension within the ArcView GIS mapping software. This required two different software packages to be purchased and installed on an operating system. The latest version of MIKE Hydro Basin, however, has its own built-in mapping software which is used to define all the information regarding the location of the water users, configuration of the flow simulation, reservoir intakes and outlets, as well as return flows.

The model has a basic input of time series data of catchment runoff for each branch. The reservoir characteristics, operational rules for each catchment, data pertinent to each water supply or irrigation scheme, and meteorological time series, as well as other information describing return flows, are further defined by additional input files. The major inputs to the model, however, are the hydrologic and water demand data. The model further has an output containing the frequency and magnitude of any water shortages as well as a simulated time-series of flows at each node that provides information regarding the performance of each reservoir and water supply schemes (Jha et al., 2003). The modelling concept of MIKE Hydro Basin is schematically displayed in Figure 2.6.

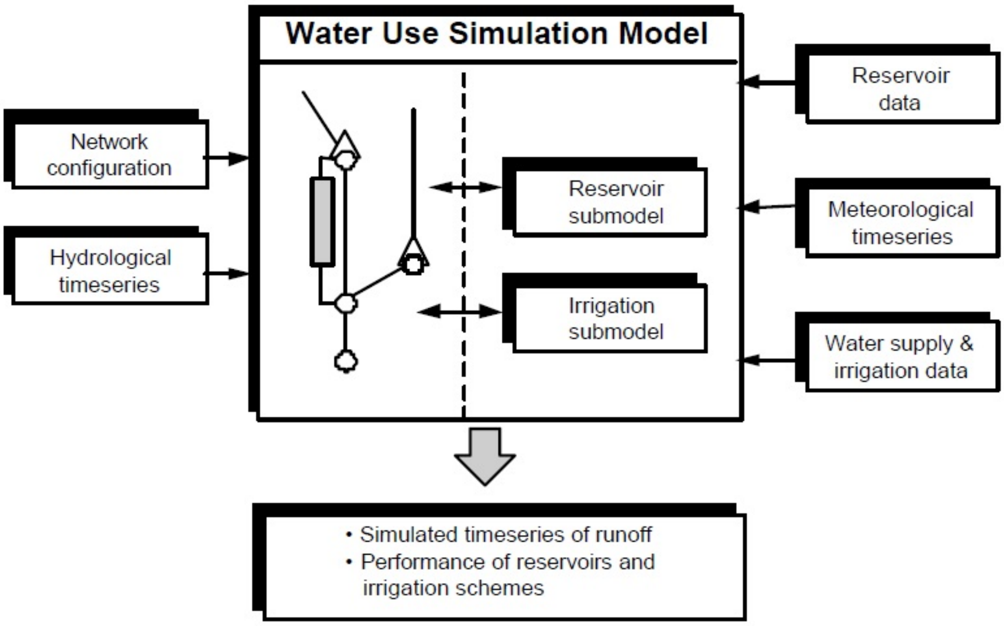

Figure 2.6: General operation of MIKE Hydro Basin water allocation model (Jha et al., 2003)

2.8.2 Model Features

According to (DHI, 2014) MIKE Hydro Basin models generally utilise a river network and sub-catchments within the specific river basin as basic model-data. A number of features can be applied depending on the type of application. Features include River routing, Water users (regular as well as Irrigation users), Hydropower and Reservoirs, Hydrology (rainfall-runoff simulations), Groundwater, Global ranking of water users, Reservoir sedimentation and Water quality options using ECO Lab.

2.8.2.1 River Network

In MIKE Hydro Basin the river networks form the basis of the hydrological system. In the model a river network is defined as a combination of connected river branches and module-specific network features, namely river branches and branch connections, river nodes, and priority nodes (DHI, 2014).

2.8.2.2 Catchment

Catchments are included in MIKE Hydro Basin to provide inflow into a river network. The runoff from a catchment can either be user-defined or it can be calculated with one of the several rainfall-runoff models available in MIKE Hydro Basin (DHI, 2014).

2.8.2.3 Water Users

Water users in MIKE Hydro Basin represent water consuming activities withdrawing water from the reservoir or river. Any number of water users can be inserted in a model setup. MIKE Hydro Basin supports two types of water users, namely regular water users (municipal, industrial, etc.) and irrigation water users (DHI, 2014).

2.8.2.4 Reservoirs

MIKE Hydro Basin accommodates multiple multi-purpose reservoir systems. The model allows individual reservoirs to simulate the performance of specified operating policies using associated operating rule curves. These define the water levels and releases at any time as a function of current water level, the desired storage volumes, demand for water and gains and losses (evaporation and precipitation) (DHI, 2014).

2.8.3 Model Limitations

MIKE Hydro Basin has certain limitations. The limitations include the lack of optimisation procedures for reservoir operation and the incapability to simulate erosion and sediment transport. Furthermore, the model is not well documented for the equations and methods it uses in the modelling of flow and water quality.

2.8.4 Stochastic Streamflow Generation

According to DHI (2014) a simulation in MIKE Hydro Basin can be executed in a simple stochastic type of mode, where the model resets the initial conditions of the system every year. The model changes the initial inflow and climatic conditions in order to simulate possible future conditions.

This form of stochastic simulation is in fact not the generation of stochastic streamflow sequences. DHI confirmed that MIKE Hydro Basin is not able to generate stochastic streamflows or conduct an automated yield analysis. The model can simply be used to simulate a hydrological system, but through scenario analysis the yields of reservoirs can be determined.

2.9 Summary

There exist many different methods and processes to calculate and generate stochastic data. Whenever stochastic data is generated and analysed for a system, it provides the possibility to identify strengths and weaknesses within a system.

In South Africa the main hydrological model in practice is the Water Resource Yield Model (WRYM). This model was created for and used by the Department of Water and Sanitation of South Africa. The model has its own built-in stochastic streamflow generator and is able to do historical and stochastic yield analyses for a hydrological system. However, an external application, now packaged as STOMSA, is still required to generate the parameters of the stochastic model.

In the literature another stochastic streamflow generator was identified namely SAMS. This generator was developed in the United States of America. In this research STOMSA and SAMS will be compared in order to determine if there is any difference between a stochastic streamflow generator that were developed and is currently used in another country and a stochastic streamflow generator that were developed and is currently used in South Africa. The process that will be followed for the comparison will be discussed in Chapter 3.

In this research the hydrological modelling framework MIKE Hydro Basin, that was developed by the Danish Hydraulic Institute (DHI), will also be analysed and compared to the WRYM. In the literature it was discovered that MIKE Hydro Basin is not able to generate and analyse its own stochastic streamflow data. For the analyses and comparison, stochastic streamflow data will be generated using STOMSA. STOMSA is the stochastic streamflow generator commenly known and used in South Africa and will therefore be used for this study. The data generated by STOMSA will be used internally in the WRYM and imported into MIKE Hydro Basin. The process that will be used for this analysis and comparison will be discussed in Chapter 3.

Chapter 3

Methodology

The literature in Chapter 2 indicates that there exist different stochastic streamflow generators along with hydrological simulation models. The focus of this research is the generation of stochastic streamflows and the use thereof within the WRYM and MIKE Hydro Basin to determine which hydrological simulation model is the best to use under certain circumstances in terms of the accuracy with which each model simulate a hydrological system, the output each model provide as well as the user-friendliness of each model.

The various processes that was used to analyse the stochastic generators, the WRYM and MIKE Hydro Basin was discussed in this chapter.

3.1 Overview

3.1.1 SAMS and STOMSA

SAMS and STOMSA was used to generate stochastic streamflow sequences, using historical streamflow data from flow station C9R002. SAMS was used to generate 100 stochastic streamflow sequences. Thereafter STOMSA was set up to use the same marginal and time-series distributions as SAMS and generate 100 stochastic streamflow sequences. STOMSA was also used to generate an additional 100 stochastic streamflow sequences, using the generators' own default marginal and time-series distributions. A graphical representation of the process is presented in Figure 3.1.

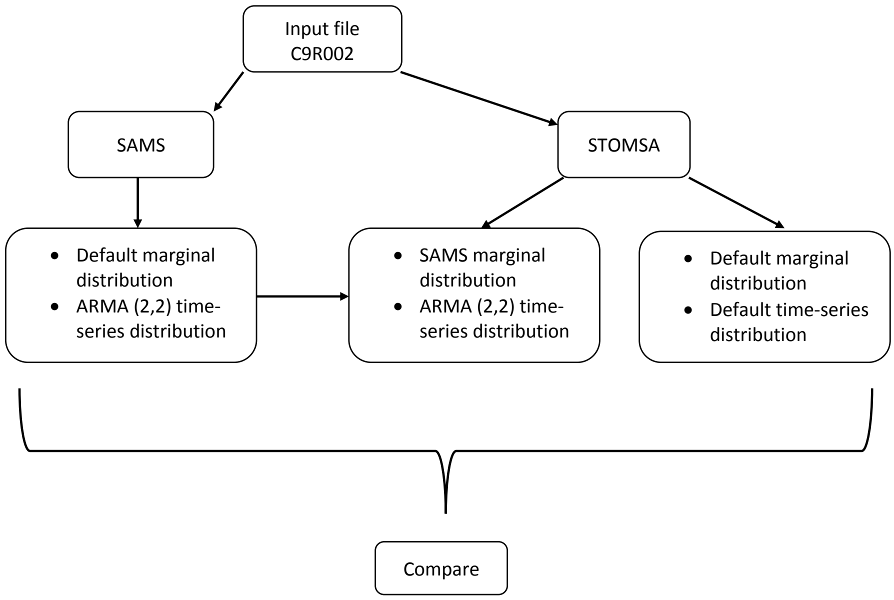

Figure 3.1: Graphical presentation of procedures followed in the analysis of SAMS and STOMSA

The data generated by SAMS and STOMSA were analysed and compared and a conclusion was made on which generator is the best to use for the prescribed data. A thorough explanation of the procedures followed in the analysis were presented in the following sections of this chapter.

3.1.2 WRYM and MIKE Hydro Basin

The WRYM and MIKE Hydro Basin were used to do historical and stochastic yield analyses for the Voëlvlei dam with historical streamflow data from flow station G1R001. STOMSA was used to generate 201 stochastic sequences for the stochastic analyses of the two models. A graphical representation of the process is presented in Figure 3.2.

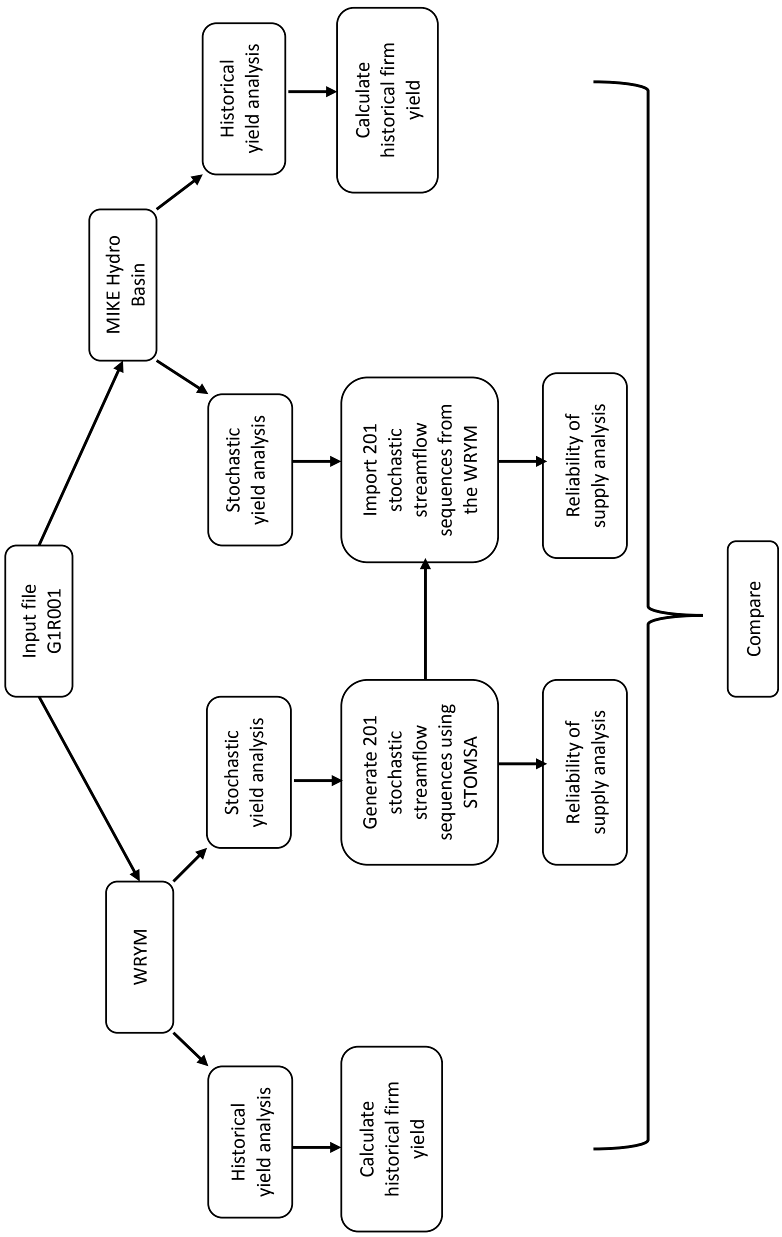

Figure 3.2: Graphical presentation of procedures followed in the analysis of the WRYM and MIKE Hydro Basin

The analyses of the WRYM and MIKE Hydro Basin were analysed and the results compared. A thorough explanation of the procedures followed in the analyses were presented in the following sections of this chapter.

3.2 Comparison of Stochastic Streamflow Generators

In Chapter 2 two stochastic streamflow generators were identified, STOMSA (Section 2.5) and SAMS (Section 2.6). It is, however, not possible to determine how the two stochastic streamflow generators will perform under the same conditions by only studying the literature. A thorough analysis of both generators is therefore required to determine which generator generates stochastic streamflow data that best suits a certain condition.

3.2.1 Historical Streamflow Data

For the purpose of the comparison between SAMS and STOMSA a set of historical streamflow data from flow station C9R002 at the Bloemhof dam, which is situated in the Vaal river in the Free State Province in South Africa, was obtained. The data file contains 75 years of historical monthly steamflow data from 1920 up to 1994 and is available in Appendix A. A graphical representation of the annual streamflows is available in Figure 3.3. The data from flow station C9R002 posses data that is unique to the climate conditions of South Africa, with streamflows varying from low in the dry months to high in the months with abundance of rain, and therefore the data from flow station C9R002 was used for the comparison of the two generators. This historical streamflow data will be used to generate stochastic streamflow sequences with SAMS and STOMSA.

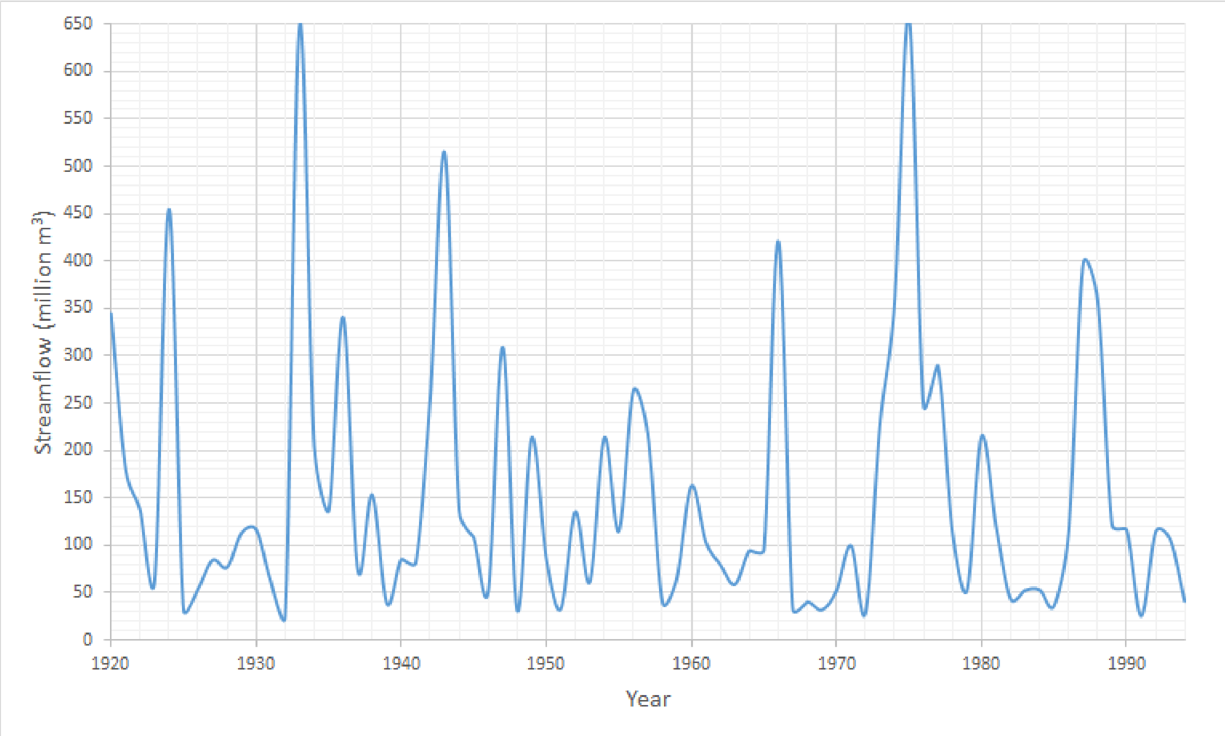

Figure 3.3: Annual historical streamflow from flow station C9R002

3.2.2 SAMS

For the stochastic streamflow analysis with SAMS, the default marginal distribution of SAMS was used to convert the historical streamflow file to a normal distribution. According to Sveinsson et al. (2007), the default marginal distribution of SAMS is the best estimated distribution for a given historical streamflow data series within SAMS.

SAMS was used to generate 100 stochastic streamflow sequences of 75 years, the same length as that of the historical streamflow series. Two sets of stochastic streamflow series were generated by SAMS. The first set of data will be generated using the annual generation model of SAMS and the second set, using the monthly generation model of SAMS. For the generation of the annual stochastic streamflow data a ARMA (2,2) time-series distribution will be used and an PARMA (2,2) for the generation of the monthly stochastic streamflow data.

3.2.3 STOMSA

For the stochastic streamflow analysis with STOMSA, the same marginal and time-series distributions used by SAMS was used to convert the historical streamflow file to a normal distribution and generate 100 stochastic streamflow sequences of 75 years. The same distributions that was used in SAMS were used in STOMSA in order to compare the results of the two generators using the same distributions while eliminating any external factors.

A second set of stochastic streamflow series was also generated using the default marginal, and time-series distributions estimated by STOMSA. According to McKenzie et al. (2004), the default marginal and time-series distributions of STOMSA are the best estimated distributions for a given historical streamflow data series within STOMSA. The seconded set of of stochastic streamflow series was generated using STOMSA in order to compare the two generators when each generator is used at that generators' optimum abilities.

3.2.4 Comparison

The generated stochastic streamflow sequences of both generators were analysed and compared in Section 4.4. With this comparison it was be possible to identify any differences between the two stochastic generators under the same conditions.

3.3 Yield Network Setup

The WRYM and MIKE Hydro Basin were used to conduct a monthly historical as well as a stochastic yield analysis. Two hydrological networks were analysed by each one of the two models.

3.3.1 Network 1

The first network consists of a reservoir receiving water from only one resource, which provides water on a monthly basis. The reservoir is connected to a yield channel and a spill channel. A graphical representation of the network is presented in Figure 3.4.

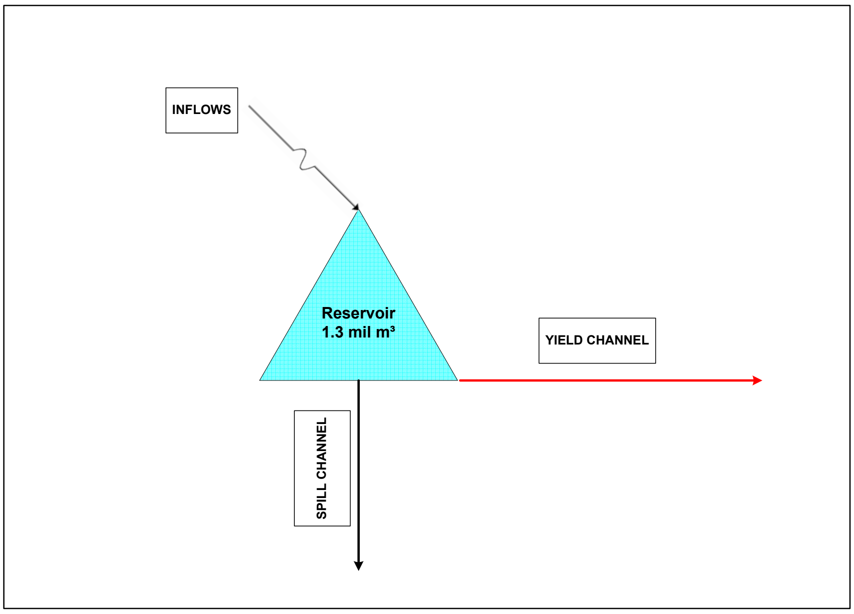

Figure 3.4: Network 1 without gains and losses

3.3.2 Network 2

The second network that was analysed by the two models is the same as the network in Section 3.3.1. The difference is that gains and losses from the reservoir surface, in the form of evaporation and precipitation, is accounted for in the second network. A graphical representation of the network is presented in Figure 3.5.

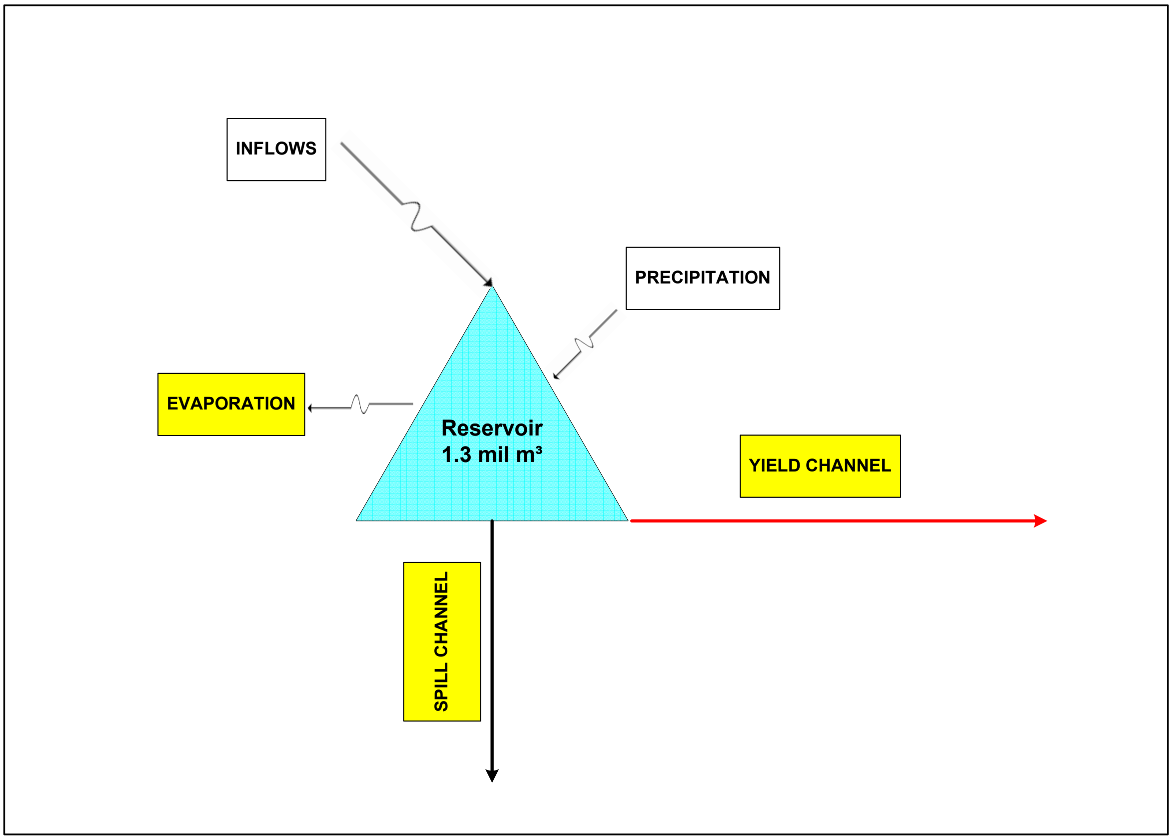

Figure 3.5: Network 2 with gains and losses

3.3.3 Reservoir Characteristics

The reservoir that was used for the analyses has certain characteristics. The reservoir has a full storage capacity of 1.3 $millionm^3$. For each analysis the reservoir started at full capacity. The relationship between the reservoir capacity and its surface area is presented in Table 3.1 and graphically presented in Figure 3.6.

Table 3.1: Physical characteristics of reservoir

Elevation (m, MASL)	Volume ($million\ m^3$)	Surface area (km^2)
FSL = 1000	1.300	0.260
980	1.040	0.208
960	0.780	0.156
940	0.520	0.104
920	0.260	0.052
DSL = 900	0.000	0.000

Where:

MASL = meter above sea level.
FSL = full storage level.
DSL = dead storage level.

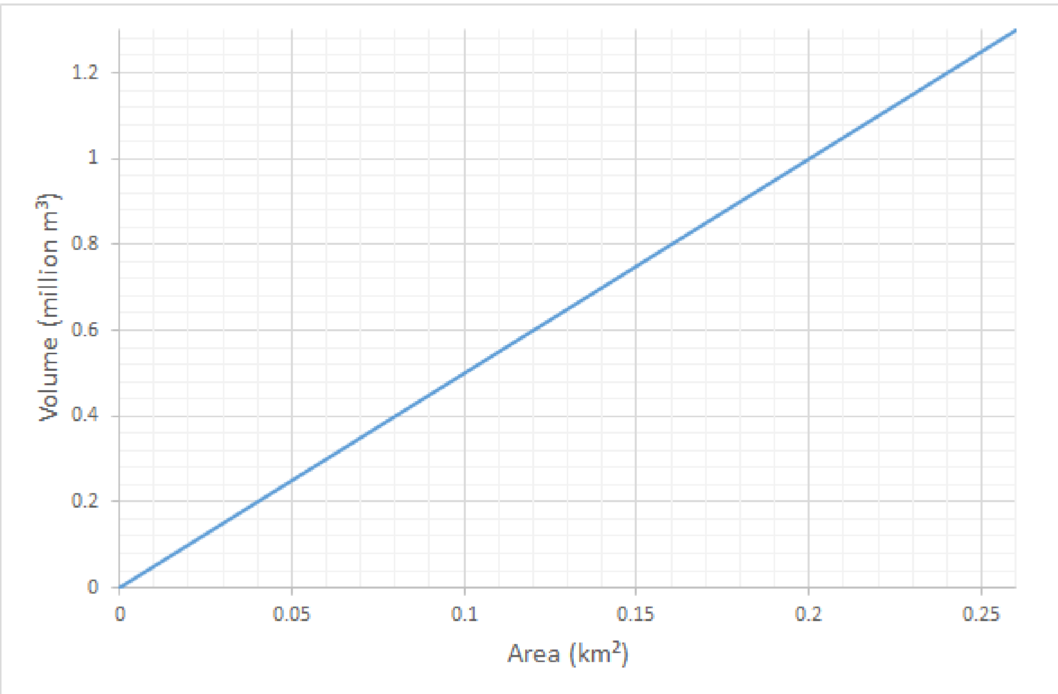

Figure 3.6: Physical characteristics of reservoir

3.3.4 Inflow to Reservoir

For the analyses of Network 1 and Network 2 a set of historical streamflow data from flow station G1R001, at the Voëlvlei dam near Tulbagh in the Western Cape of South Africa, was used as inflow data into the reservoir. The data file contains 35 years of historical monthly streamflow data from October 1968 up to September 2003 and is available in Appendix D.1. A graphical representation of the annual streamflows is presented in Figure 3.7.

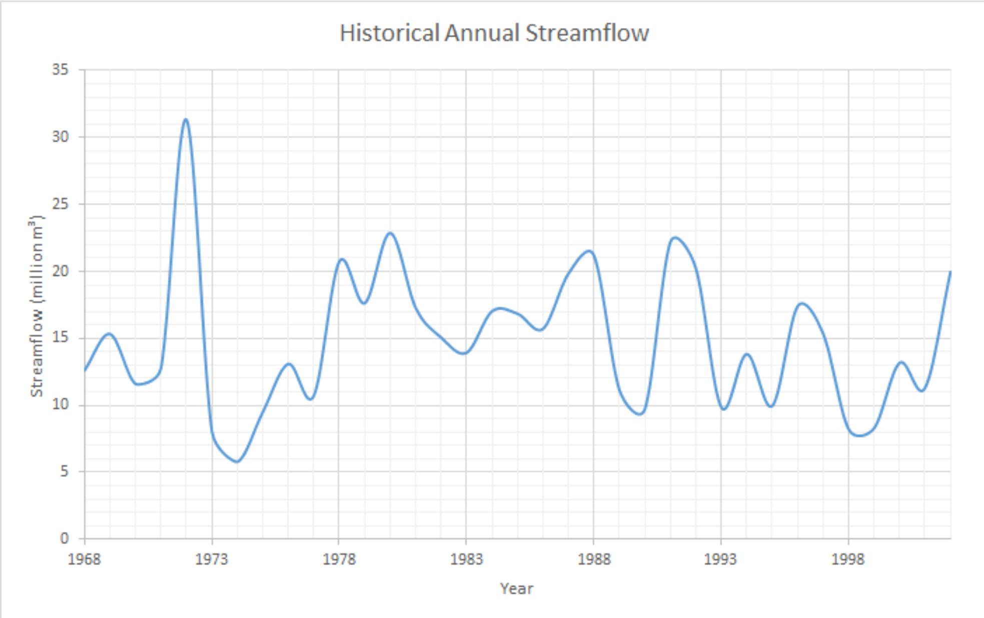

Figure 3.7: Annual historical streamflow from flow station G1R001

3.3.5 Channels

The yield channel in Network 1 and Network 2 was used to abstract water on a monthly basis from the reservoir. This channel has no restrictions.

The spill channel in Network 1 and Network 2 was used in the case where the reservoir is at capacity to divert water that caused the reservoir to spill. This channel has no restrictions.

3.3.6 Evaporation

The analyses of Network 2 requires monthly evaporation data from the reservoir. The S-pan mean annual evaporation (MAE) recorded for the Voëlvlei dam at flow station G1R001 was found to be 1635 mm. This S-pan MAE had to be distributed monthly into open water evaporation. The monthly distribution of the S-pan evaporation of Voëlvlei dam was obtained and is available in Table 3.2 along with the open water pan factors.

Table 3.2: Evaporation distribution

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
S-Pan Evaporation	8.70%	12.10%	14.80%	15.10%	12.50%	11.50%	7.10%	4.00%	2.60%	2.60%	3.60%	5.40%
Pan Factors	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.8	0.8	0.8
S-Pan x Open water	6.96%	9.68%	11.84%	12.08%	11.25%	10.35%	6.39%	3.60%	2.34%	2.08%	2.88%	4.32%

The evaporation for each month from the reservoir was calculated using Equation 3.1 and the results are available in Table 3.3.

$$Monhtly\ Evaporation\ (mm) = MAE \times S - Pan\ Evaporation \times Pan\ Factor \tag{3.1}$$

Table 3.3: Monthly evaporation from reservoir

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Evaporation (mm)	113.80	158.27	193.58	197.51	183.94	169.22	104.48	58.86	38.26	34.01	47.09	70.63

3.3.7 Precipitation

The analyses of Network 2 requires monthly precipitation data from the reservoir. A historical rainfall file from October 1968 to September 2003 was therefore required, since the historical streamflow file from flow station G1R001 contains streamflow data from October 1968 to September 2003. The Voëlvlei dam falls within rainfall zone G1B. The recorded mean annual precipitation (MAP) for rainfall zone G1B was found to be 475 mm in the WR2012. The monthly distribution of the rainfall in rainfall zone G1B was also obtained as a percentage of the MAP from the WR2012 and is presented in Appendix D.2. To create the historical rainfall file the MAP was multiplied with the monthly distribution. The created historical rainfall file is presented in Appendix D.3.

3.4 WRYM

In Section 2.7 it was stated that the latest version of the WRYM is incorporated in the Water Resource Modelling Framework (WRMF). In this research the WRMF Version 4.3.0.0 was used to do historical as well as stochastic yield analyses on Network 1 and Network 2 described in Section 3.3.

3.4.1 Historical Yield Analysis

Network 1 and Network 2 were analysed historically. The two analyses were used to identify the historical firm yield of each network. The historical firm yields were determined using the built-in historical firm yield calculator of the WRYM.

3.4.2 Stochastic Yield Analysis

After the historical yield analysis of each network was completed, a stochastic yield analysis of the network was done. In the literature, in Section 2.7.3, (*WRMF Manual* 2010) recommends that 201 stochastic sequences should be used for a long-term stochastic yield analysis. Therefore 201 monthly stochastic streamflow sequences were generated from the historical streamflow file, described in Section 3.3.4, for this analysis. Each sequence is 35 years long, which is the same length as that of the historical streamflow file.

3.4.2.1 Stochastic Streamflow Generation

The 201 stochastic sequences were generated within the WRYM, which uses STOMSA as stochastic streamflow generator. For this stochastic streamflow generation, the WRYM requires a parameter file that contains all the statistical parameters of the historical streamflow file, namely the PARAM.DAT file (Section 2.5.1). This parameter file was created in the stand alone version of STOMSA that was used in Section 3.2. The parameter file is available in Appendix E.

3.4.2.2 Reliability of Supply

The generated stochastic sequences were analysed for Network 1 and network 2, using the calculated historical firm yield of each network as the annual target draft.

The WRYM is able to calculate the long-term risk of failure, reliability of supply as well as the recurrence interval of failures internally for the network.

3.5 MIKE Hydro Basin

MIKE Hydro Basin described in Section 2.8 was used to do historical and stochastic yield analyses on Network 1 and Network 2 described in Section 3.3.

3.5.1 Historical Yield Analysis

Network 1 and Network 2 were first analysed historically. The two analyses were used to identify the historical firm yield of each network. The two historical firm yields were determined manually by increasing the amount of water that is abstracted annually from the reservoir until the reservoir reaches a capacity of 0 million m^3. The largest amount of water that can be abstracted from the reservoir, without the reservoir reaching a capacity of 0 million m^3 was taken as the historical firm yield. The historical firm yields were compared to the historical firm yields calculated by the WRYM.

3.5.2 Stochastic Yield Analysis

After the historical and stochastic yield analysis of each network were completed in the WRYM, a stochastic yield analysis of each network were done in MIKE Hydro Basin. For the stochastic analysis the 201 stochastic streamflow sequences generated in the WRYM were imported into MIKE Hydro Basin as historical streamflow files.

3.5.2.1 Network 1

In the analysis of Network 1, only the 201 stochastic streamflow files were imported into the model one by one. The model will thus be executed 201 times and for each stochastic streamflow file, the outflow data through the yield channel was recorded. The recorded outflow data was used to calculate the base yield (Section 2.3) for each sequence.

3.5.2.2 Network 2

For the analysis of Network 2, 201 rainfall sequences were required as input files along with the 201 stochastic streamflow files. The rainfall sequences were calculated by distributing the MAP monthly.

In order to distribute the MAP monthly, a monthly distribution of the mean annual runoff (MAR) had to be determined. The MAR is the average annual streamflow of the historical streamflow file and was calculated to be 14.847 million m^3. For each stochastic streamflow file the stochastic streamflow for each month was calculated a fraction of the historical MAR (14.847 million m^3) and the calculated fraction was multiplied with the MAP (475mm) to obtain the stochastic precipitation for that month. An example of the calculation of the stochastic precipitation of sequence 1 for October 1968 is available in Equation 3.2.

$$\begin{aligned} Historical\ Month\ Rainfall &= \frac{Month\ Streamflow}{MAR} \times MAP \\ &= \frac{1.28}{14.847} \times 475 \\ &= 40.96\ mm \end{aligned} \tag{3.2}$$

In the analysis of Network 2, the same procedure described in Section 3.5.2.1 was used to calculate the base yield for the 201 stochastic streamflow sequences.

3.5.2.3 Risk of Failure, Reliability of Supply and Recurrence Interval of Failures

The generated stochastic sequences were analysed for Network 1 and Network 2, using the calculated historical firm yield from the WRYM (Section 3.4.1) of each network as the annual target draft.

The long-term risk of failure and long-term reliability of supply calculations along with the recurrence interval of failures for each network were calculated using Equations 2.12, 2.13 and 2.14 from Section 2.7.3.

3.6 Summary

The two stochastic streamflow generators, SAMS and STOMSA, were used to generate stochastic streamflow sequences from the historical streamflow file of flow station C9R002. The generated sequences were analysed and compared in Chapter 4.

The WRYM was used to do historical and stochastic yield analyses of Network 1 and Network 2. The analyses and results are discussed in Chapter 5.

MIKE Hydro Basin was used to do historical and stochastic yield analyses of Network 1 and Network 2. The analyses and results are discussed in Chapter 6.

A graphical summary of the procedures that were followed in the analysis process of the WRYM and MIKE Hydro Basin, as described in Chapter 3, is presented in Figure 3.2.

The results form the historical and stochastic yield analyses from the WRYM and MIKE Hydro Basin are discussed and compared in Chapter 7.

Chapter 4

Comparison of Stochastic Streamflow Generators STOMSA and SAMS

In this chapter the two stochastic streamflow generators that were discussed in Sections 2.5 and 2.6, STOMSA and SAMS, were analysed and compared. The analysis was done using a set of historical streamflow data as a basis and generating stochastic streamflows with each generator. Various methods were used to analyse the two generators in-depth. These analyses were used to compare the two generators.

4.1 Test Data

The historical streamflow data, described in Section 3.2.1, was analysed and both the annual and monthly statistical parameters were calculated. The monthly statistical parameters are presented in Table 4.1 and the annual statistical parameters are presented in Table 4.2.

Table 4.1: Monthly statistical parameters of historical streamflow test data from flow station C9R002

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Mean	6.320	14.590	16.932	26.844	28.054	31.755	13.240	5.472	2.455	1.914	2.072	4.046
Median	1.460	4.660	9.170	12.030	10.660	11.610	4.650	1.640	1.290	1.140	1.060	0.890
Standard Deviation	12.311	29.348	21.635	49.496	44.215	59.115	19.964	10.752	2.905	1.923	3.765	13.818
Coefficient of Variance	1.948	2.012	1.278	1.844	1.576	1.862	1.508	1.965	1.183	1.005	1.817	3.415
Skewness	3.150	4.271	2.024	5.021	2.544	3.153	2.339	3.712	2.861	2.539	6.234	6.205
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	60.020	199.210	102.700	367.630	230.190	295.930	97.290	57.700	15.450	11.240	30.650	103.240

Table 4.2: Annual statistical parameters of historical streamflow data from flow station C9R002

Mean	153.693
Median	108.310
Standard Deviation	141.194
Coefficient of Variance	0.919
Skewness	1.785
Minimum	24.980
Maximum	658.440

4.2 SAMS

SAMS is a user friendly stochastic streamflow generator that allows the user to choose between various data transformation (marginal) distributions as well as mathematical (time-series) distributions. SAMS also allows the user to either generate annual or seasonal (e.g. monthly) data. The generator further enables the user to view various data plots within the model and export data directly to a Microsoft Excel spreadsheet for further calculations.

SAMS was used to generate stochastic streamflow series from the historical streamflow data from flow station C9R002. The processes used during the generation of the data as well as the results obtained were discussed in Sections 4.2.1 and 4.2.2.

4.2.1 Modelling

For the purpose of this research the default marginal distribution of SAMS was used to generate 100 stochastic streamflow sequences, since it is the best estimated marginal distribution for the specific historical streamflow data by SAMS. In Section 2.7.3 it is stated that 201 stochastic sequences for a long-term stochastic yield analyses. The purpose of this study, however, was only to compare the data generated by the two generators and therefore only 100 stochastic streamflow sequences were generated.

Two sets of data were generated using both the annual and seasonal data generation models.

During the modelling process the following steps were followed:

1. The historical data file was imported into SAMS.

2. A model had to be found that could be used to transform the annual total flows and monthly flows to normal distributions in order to determine the appropriate marginal distributions for the historical streamflow sequence. The 3-parameter log normal (LN3) distribution was used in this case. SAMS found this distribution to be the most efficient manner to transform the historical streamflows into a normal distribution.
3. After the appropriate marginal distribution had been selected, a time-series distribution had to be determined which best represents the serial correlation exhibited by the resulting data set. An ARMA(2,2) model was used to generate the annual data and a PARMA(2,2) model was used to generate the monthly data.
4. The final step was to generate stochastic streamflow sequences. In this study 100 streamflow sequences of 75 years, the same length as that of the historical series, were generated.

4.2.2 Results: SAMS

After the stochastic streamflow sequences were generated, the monthly data was combined to create a new set of annual data. The statistical parameters of both the annual generated data as well as the annual data composed of monthly data for each one of the 100 generated sequences were calculated. The average of these parameters is presented in Table 4.3

Table 4.3: Average annual and monthly statistical parameters of the stochastic streamflow sequences generated by SAMS using the LN3 distribution

	Annual	Seasonal
Mean	155.00	163.96
Median	104.64	111.75
Standard Deviation	160.87	178.02
Skewness	2.74	2.96
Minimum	20.43	16.58
Maximum	962.75	1114.99

Monthly generated stochastic streamflow data of five randomly selected sequences namely sequence 11, 28, 40, 63 and 85 wase selected for further analyses. An extract of the five data sets (October 1949 to September 1959 from sequence 11) are presented in Figure 4.1. The other four sequences are presented in Appendix C.1.

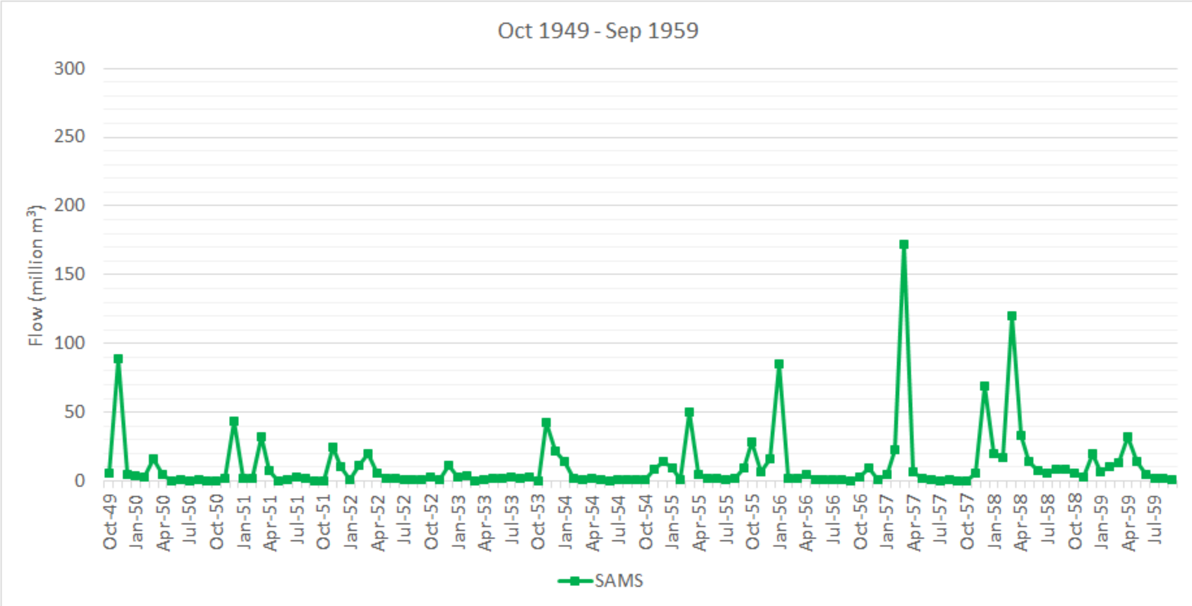

Figure 4.1: SAMS generated streamflow data sequence 11 using a 3-parameter log-normal distribution

4.3 STOMSA

STOMSA was used to generate stochastic streamflow series from the historical streamflow data from flow station C9R002. STOMSA is an user friendly stochastic generator that allows the user to choose between various data transformation (marginal) distributions as well as mathematical (time-series) distributions. For the purpose of this research, however, the 3-parameter log-normal marginal distribution and a ARMA (2,2) time-series distibution was used, the same as that used in the stochastic streamflow generation by SAMS.

Stochastic streamflows were generated using the default marginal, and time-series distributions estimated by STOMSA. According to McKenzie et al. (2004), these are the best estimated distributions for a given historical streamflow data series in STOMSA.

In both cases 100 stochastic streamflow sequences were generated. The processes used during the generation of the data as well as the results obtained were discussed in Sections 4.3.1 and 4.3.2.

4.3.1 Modelling

During the modelling process the following steps were followed:

1. The historical data file was imported into STOMSA.
2. The key stations had to be selected. The key stations, however, is only applicable when multi-site stochastic analyses are required. Since data from only one flow station was used in this comparison, that station was set to be the key station.

3. A model had to be found that could be used to transform the annual total flows to a normal distribution in order to determine the appropriate marginal distribution for the historical streamflow sequence, as discussed in Section 2.5.1.2. A 3-parameter log-normal (LN3) distribution was used to transform the annual historical streamflows to a normal distribution for the stochastic streamflow generation by STOMSA. The LN3 marginal distribution was used in the stochastic streamflow generation by SAMS in Section 4.2.1 and the same distribution was used for the stochastic streamflow generation by STOMSA for consistency.

   A second set of stochastic sequences was also generated, using a 4-parameter bounded marginal distribution (SB4). STOMSA selected SB4 marginal distribution to be the best marginal distribution to transform the historical streamflows into a normal distribution. The second set of stochastic streamflow sequences were generated by STOMSA to compare the data generated by STOMSA and SAMS when each generator is used at its optimum abilities.

4. After the marginal distribution was selected, a time-series distribution had to be determined which best represents the serial correlation exhibited by the resulting data set. An ARMA(2,2 time-series distribution was used to present the serial correlation. The ARMA(2,2) time-series distribution used in the stochastic streamflow generation by SAMS in Section 4.2.1 and the same distribution was used for the stochastic streamflow generation by STOMSA for consistency. The ARMA (2,2) time-series distribution was also estimated by STOMSA to be the best time-series distribution for the specific data set and was used to generate the second set of stochastic streamflows.

5. The final step is to generate the two sets of stochastic streamflow sequences, using the two different marginal distributions. It was decided to generate 100 streamflow sequences of 75 years, the same length as that of the historical series and that generated with the SAMS generator.

4.3.2 Results: STOMSA

After the two sets of stochastic streamflow sequences were generated, the annual statistical parameters for each one of the 100 generated sequences were calculated. The average of these parameters is available in Table 4.4

Table 4.4: Average annual statistical parameters of the stochastic streamflow sequences generated by STOMSA

Marginal distributions	**SB4**	**LN3**
Mean	154.97	165.04
Median	102.14	97.25
Standard Deviation	140.35	211.80
Skewness	1.56	3.49
Minimum	26.11	25.50
Maximum	628.56	1361.89

Generated stochastic streamflow data of five randomly selected sequences namely sequence 11, 28, 40, 63 and 85 as selected for further analyses. An extract of these data sets (October 1949 to September 1959 from sequence 11) are presented in Figures 4.2 and 4.3. The other four sequences are presented in Appendix C.2.

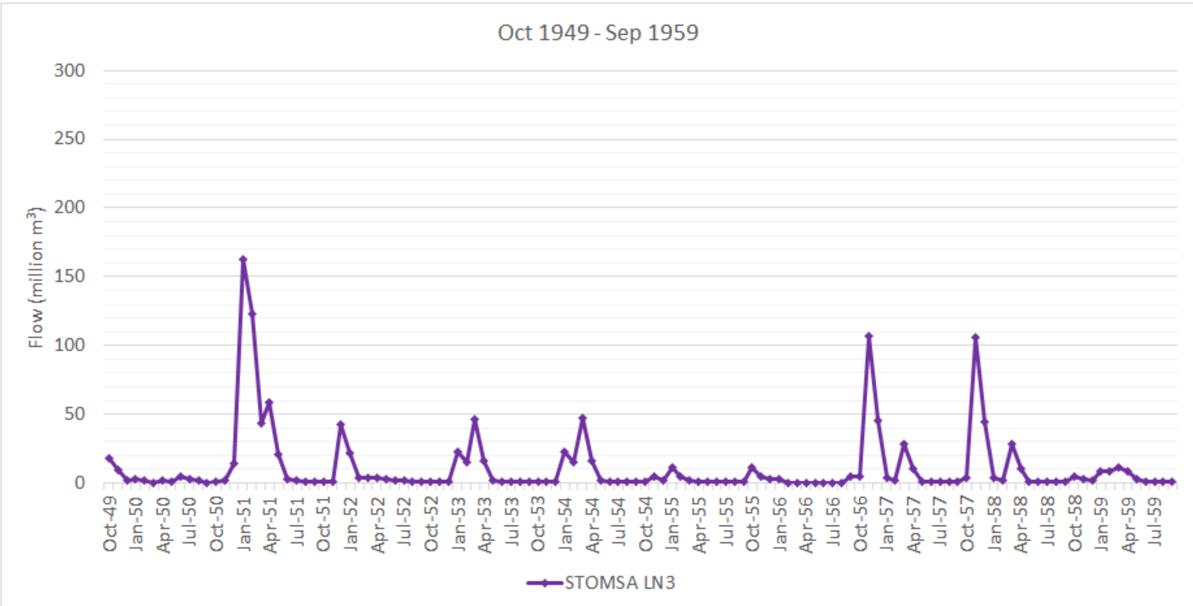

Figure 4.2: STOMSA generated streamflow data sequence 11 using a 3-parameter log-normal distribution

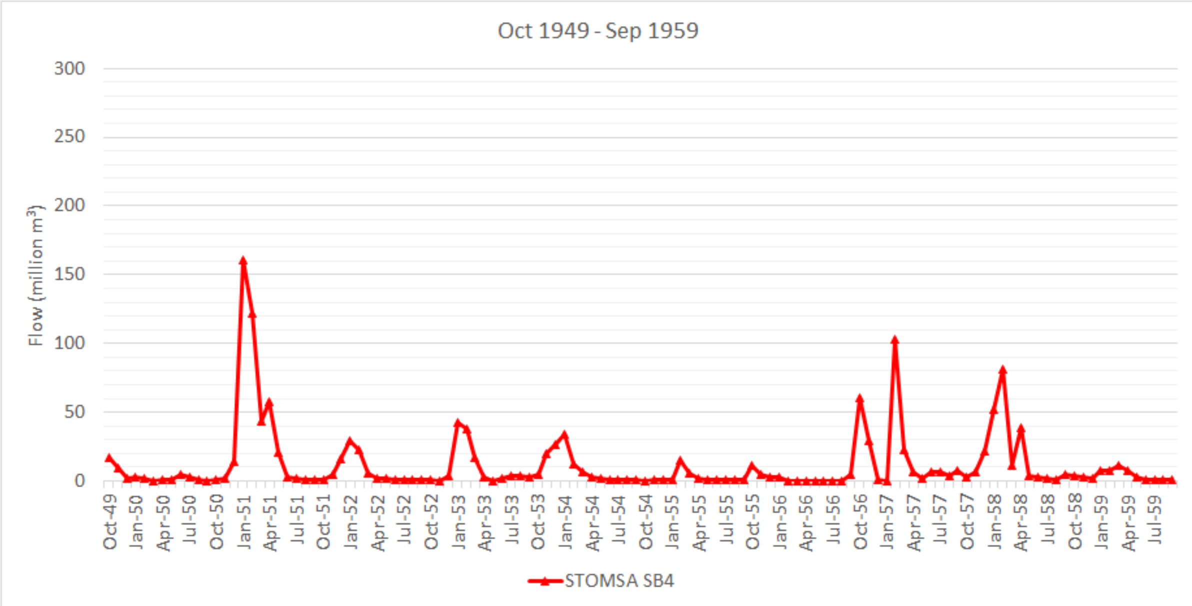

Figure 4.3: STOMSA generated streamflow data sequence 11 using a 4-parameter bounded distribution

4.4 Comparison

With all the stochastic data generated, the two generators, SAMS and STOMSA, were compared against each other and the historical data. The comparison provides an indication of how different stochastic streamflow generators process the same data. The comparisons were discussed in Sections 4.4.1 to 4.4.3.

4.4.1 Box and Whisker Plots

Before the two generators could be compared, the data generated had to be validated. This was done using a box and whisker plot as described in Section 2.5.1.7.

The same method used in STOMSA to set up the box and whisker plot was used in this study. The first step was to crush the 100 generated data sequences into two single data sets for both generators. This was done by creating a set of data for each generator which was the average of the 100 generated sequences. These averages were obtained by adding up each month of each year of all 100 sequences (e.g. Jan 1920 of sequence one + Jan 1920 of sequence 2 + Jan 1920 of sequence ...) and dividing it by 100. The two crushed data sets which were created (STOMSA and SAMS) are available in Appendix B.

After the crushed data sets were created, the median, first quartile, third quartile, minimum and maximum values for each month had to be determined for each set. These values were used to set up the box and whisker plots for both generators and are presented in Figures 4.4 and 4.5.

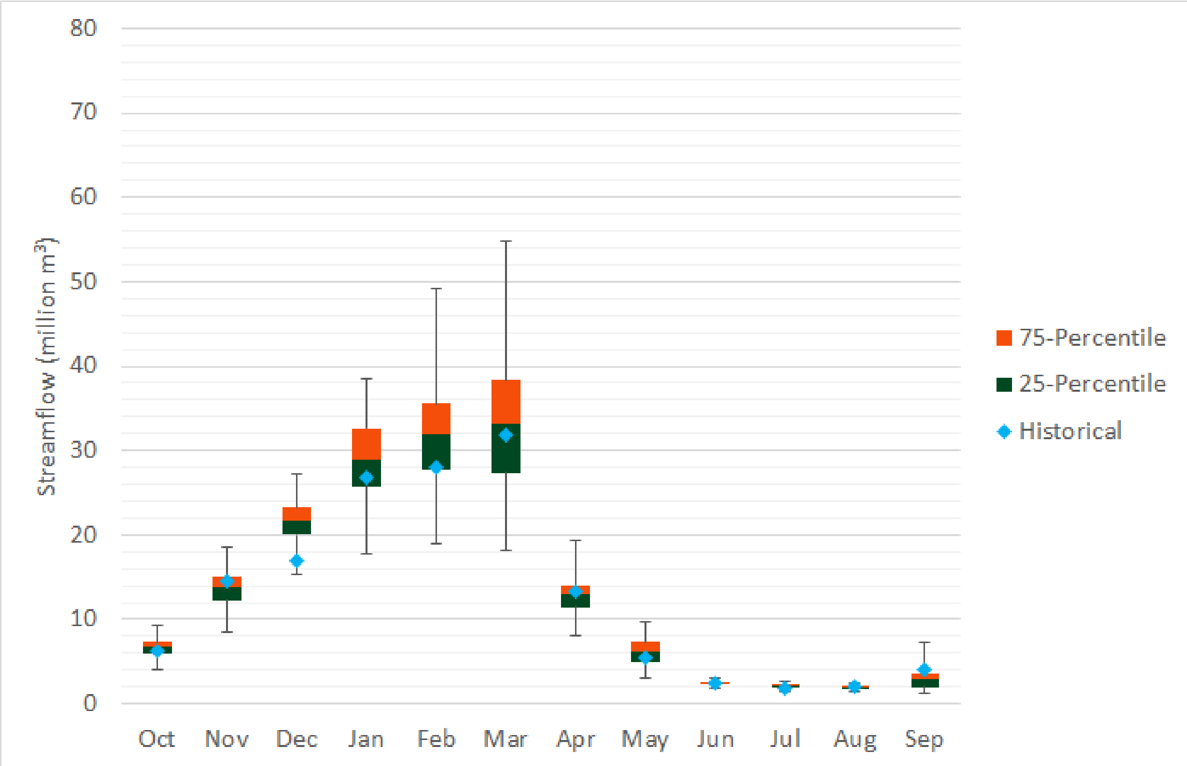

Figure 4.4: Box and whisker plot for STOMSA using an LN3 marginal distribution

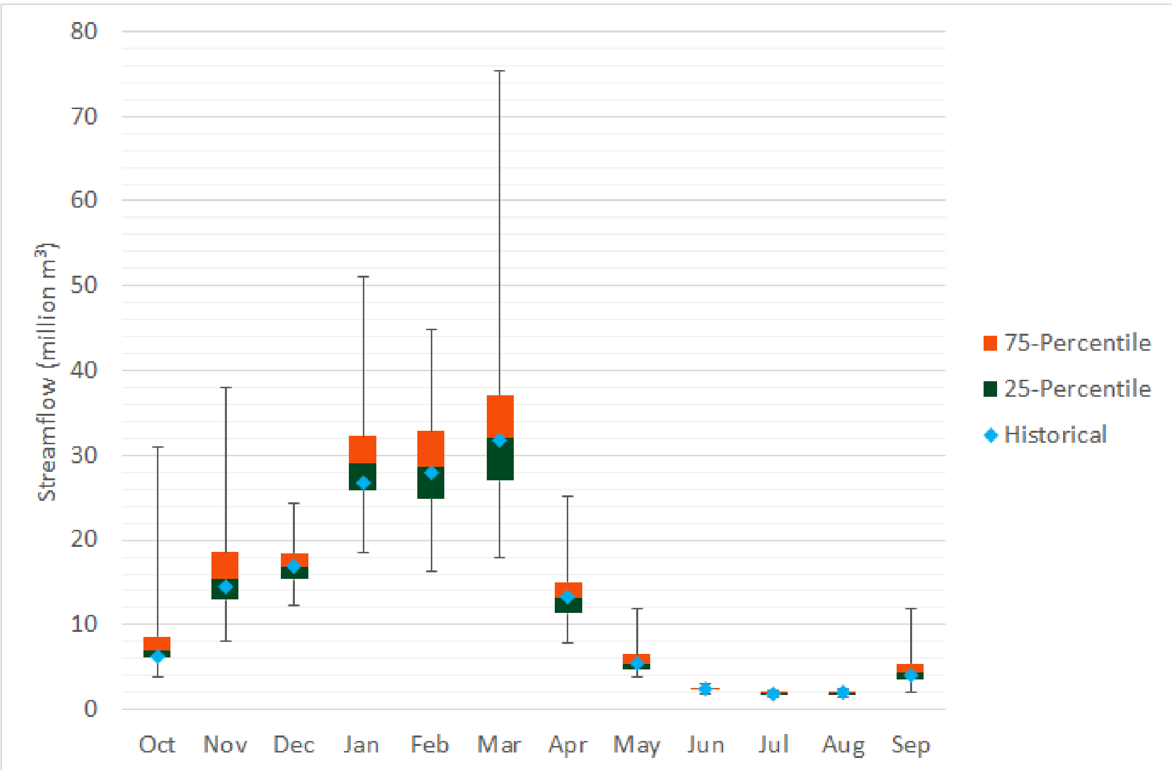

Figure 4.5: Box and whisker plot for SAMS

In Section 2.5.1.7, it is stated that generated stochastic streamflow values are acceptable if the historical value lies between the 25 and 75 percentiles. Section 2.5.1.7 also that if the historical value lies outside the 25 and 75 percentiles the errors and anomalies should be evaluated individually to ensure that they are small enough not to possess a significant influence on the overall result of the analysis.

From Figure 4.4 it is seen that all the values generated by STOMSA using an LN3 marginal distribution are acceptable, except for December. In December the historical streamflow lies below the 25 percentile. The reason is that some extremely low flows (outliers) were recorded for December over the 75 year period of the historical sequence which resulted in an exceptionally low average historical streamflow for December. The error made by the generator was, however, small and the only error in the data set and therefore all the generated stochastic sequences were accepted as valid. The values generated by SAMS in Figure 4.5 all lie between the 25 and 75 percentiles and can therefore be accepted to be valid.

When Figures 4.4 and 4.5 are compared, it is clear that there are much more outliers in the stochastic streamflows generated by SAMS than the streamflows generated by STOMSA.

4.4.2 Random Sequences

The best way to compare the generated stochastic streamflow data with the historical streamflow data was to compare one generated stochastic sequence at a time with the historical data. For the purpose of this study five random sequences were selected and compared individually with the historical data. The five selected sequences were also used for comparison between the two different generators. Only five random sequences were analysed as each generator generates random streamflow sequences using the same historical flow file. The conditions and distributions used for each generator were also kept exactly the same as explained in Sections 4.2 and 4.3. Any differences between the two generators would already be present if only one sequence was to be analysed and therefore the analyses of five sequences would be sufficient to conduct an acceptable comparison between the two generators.

There was, however, no manner in which to make a controlled selection of sequences. If for example a sequence generated using SAMS has a high average annual streamflow, it does not mean that the same sequence generated by STOMSA would also have a high average annual streamflow. If for instance five high, medium and low average annual streamflow sequences for each set of generated stochastic sequences were chosen, it would mean that nearly 30 of the 100 sequences would have to be analysed for each generator and therefore only five random sequences were selected for the analyses.

The selection was done completely at random without prior knowledge of the statistical parameters of the sequences. Both models generate completely random data through internal mathematical calculations which cannot be manipulated in any other way than to change the marginal or time-series distributions of the generator.

It was decided to use the same five randomly selected sequences for comparison (11, 28, 40, 63 and 85) that were used in Section 4.2.2. An extract of these data sets (October 1949 to September 1959 from sequence 11), along with the historical sequence, is presented in Figure 4.6. The other four sequences are presented in Appendix C.3.

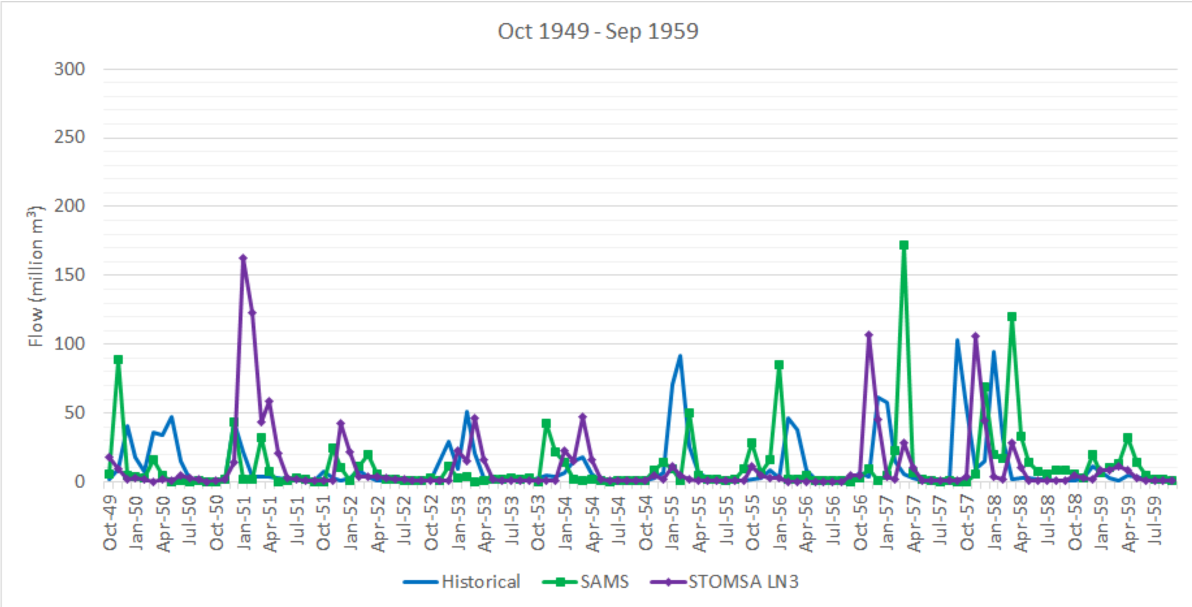

Figure 4.6: Generated stochastic streamflow sequence 11 and historical streamflow sequence

It is clear from the data plots in Figure 4.6 and Appendix C.3 that both SAMS and STOMSA are efficient stochastic streamflow generators. Stochastic data series should provide data that could be obtained in the future and should therefore correlate with the historical data. If there was no legend on each graph for instance, it would be impossible to tell which line represented the historical streamflows since both stochastic generators produced logical data sequences that could happen in the future. It can also be seen from the graphs that SAMS has outliers which indicate a bigger variance in flow over a short period of time.

For further analyses the statistical parameters of the five selected sequences were calculated and are presented in Table 4.5.

Table 4.5: Statistical parameters of five selected stochastic sequences and historical sequence

		Sequence 11		Sequence 28		Sequence 40		Sequence 63		Sequence 85	
	Historical	SAMS	STOMSA	SAMS	STOMSA	SAMS	STOMSA	SAMS	STOMSA	SAMS	STOMSA
Mean	153.69	121.60	179.26	182.91	187.52	163.79	160.06	164.12	176.52	167.26	135.32
Median	108.31	95.07	102.63	116.04	91.59	116.20	99.77	116.12	106.32	124.31	104.69
Standard Deviation	141.19	93.50	338.93	185.66	264.17	164.91	168.29	144.49	259.22	142.24	108.24
Skewness	1.79	1.76	6.93	2.23	3.82	2.73	2.72	2.56	4.28	2.98	1.87
Minimum	24.98	9.11	24.22	13.31	23.93	19.81	24.65	13.94	25.63	22.49	27.38
Maximum	658.44	528.18	2857.94	1050.67	1702.01	984.10	935.85	882.37	1740.15	966.92	598.17

The mean of generated stochastic sequences of both SAMS and STOMSA varies for the five selected sequences and tends to be higher in some cases and lower in other cases than that of the historical data. The standard deviation presents the same variation. If the maximum value for each sequence is considered, then it become evident that in most cases the SAMS and STOMSA models have maximum values greater that that of the historical data, and in some cases three to four times greater.

Even though the sequences generated using SAMS have more acceptable statistical parameters, that are closer to the statistical parameters of the historical sequence, there is not a definite correlation between the streamflows generated by the two generators and the streamflows of the historical sequence.

4.4.3 Average Annual Sequence Analyses

The generated streamflow data sets were further analysed by calculating an average annual flow for each generated sequence. The annual streamflow sequences were used for further comparison between the two generators.

The average annual streamflow for each sequence was calculated and graphically presented, along with the average annual streamflow of the historical data, in Figure 4.7.

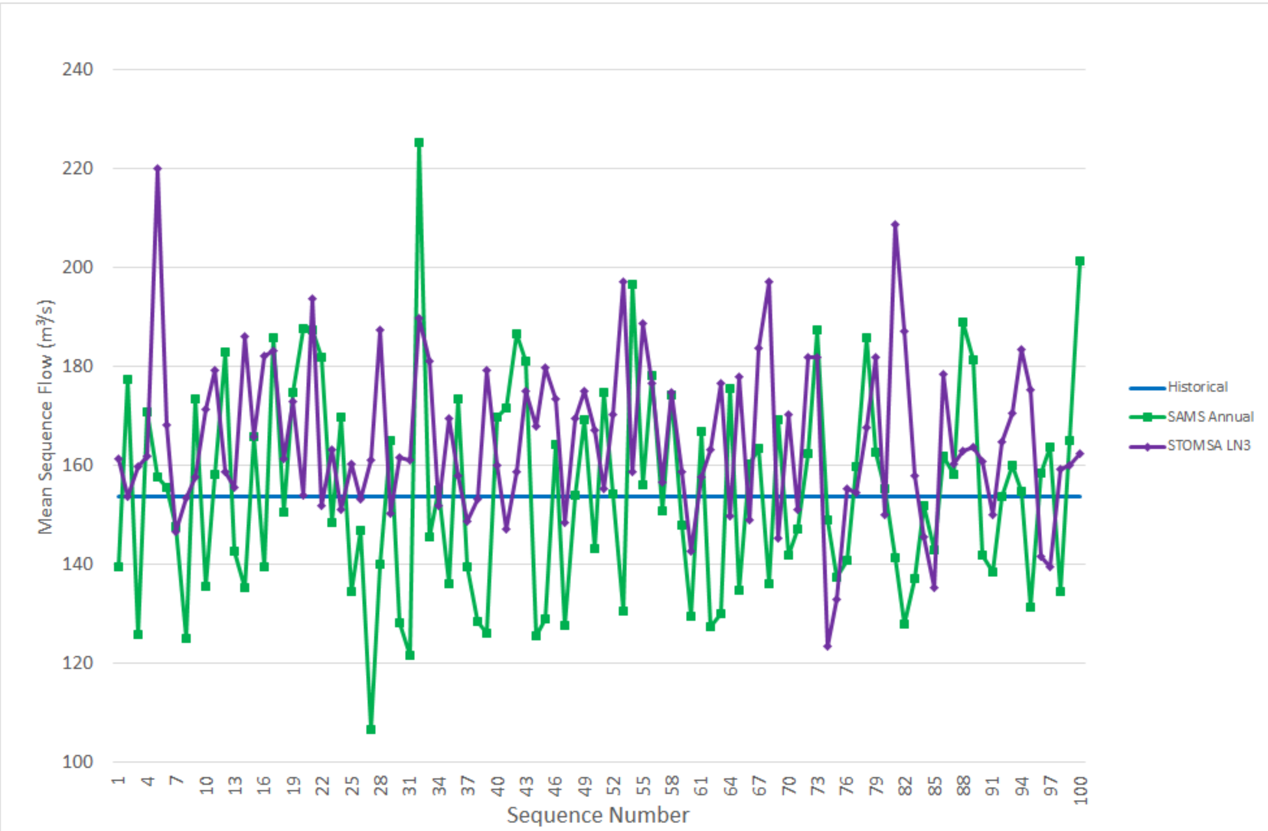

Figure 4.7: Average annual flow per sequence

From Figure 4.7 it is evident that there is a large variance between the sequences of SAMS, with one sequence having a high average annual streamflow and the next a low average annual streamflow. Large variances between the streamflow sequences generated by STOMSA, however, is not evident.

This data was further evaluated by composing the statistical parameters of the average annual streamflows of each model. The statistical parameters are presented in Table 4.6.

Table 4.6: Statistical parameters of the average annual generated stochastic streamflows

	SAMS	STOMSA
Mean	155.00	165.04
Standard Error	2.12	1.61
Median	154.51	161.57
Standard Deviation	21.18	16.11
Sample Variance	448.46	259.46
Skewness	0.43	0.53
Minimum	106.68	123.66
Maximum	225.24	219.92

From the statistical parameters in Table 4.6 it is clear that no large difference exists between the mean streamflows of SAMS, STOMSA and the average annual historical streamflow (153.69 million m^3/a. This is an indication that both models generate acceptable stochastic sequences. If the standard deviation, standard error and sample variance are considered, then it can be argued that there are bigger variances between the average annual flows of the sequences generated by SAMS than that of STOMSA.

4.4.4 STOMSA SB4

Stochastic sequences were generated by STOMSA using a 4-parameter bounded marginal distribution (SB4) and analysed. In Section 4.3.1 it was stated that STOMSA found this distribution to be the best marginal to transform the historical streamflows into a normal distribution.

The first step in this analysis was to validate the data generated by STOMSA using an SB4 marginal distribution. This was done using the method described in Section 4.4.1 to create a box and whisker plot, which is presented in Figure 4.8.

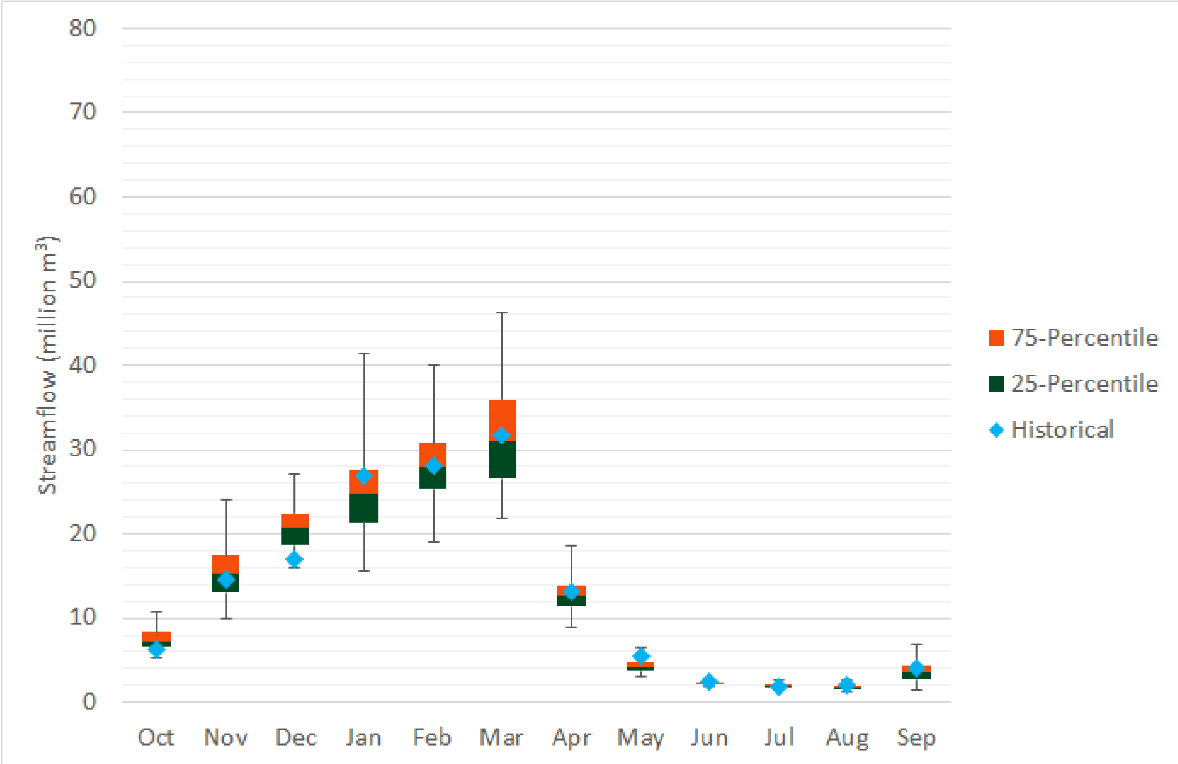

Figure 4.8: Box and whisker plot for STOMSA using an SB4 marginal distribution

From Figure 4.8 it is seen that all the values generated by STOMSA using an SB4 marginal distribution are acceptable, except for December which lies below the 25 percentile. The error made by STOMSA is the same as explained in Section 4.4.1. The error is, however, small enough to be ignored and therefore all the generated values were accepted as valid.

It is clear from Figure 4.8 that there is not such a big variance in the generated stochastic monthly streamflow in comparison with the stochastic monthly flow generated using the SAMS model, Figure 4.5, where a large number of outliers are present.

The results obtained for the sequences generated using STOMSA with an SB4 marginal distribution in Section 4.2.2, were also compared with the results from the sequences generated using SAMS and STOMSA with an LN3 marginal distribution. The same five random sequences, as discussed in Section 4.4.2, were used in the comparison.

Figure 4.9 presents an extract of all the data sets (October 1949 to September 1959 from sequence 11) along with the historical sequence. The other four sequences are presented in Appendix C.4. The statistical parameters of the five selected sequences were also calculated and are available in Table 4.7.

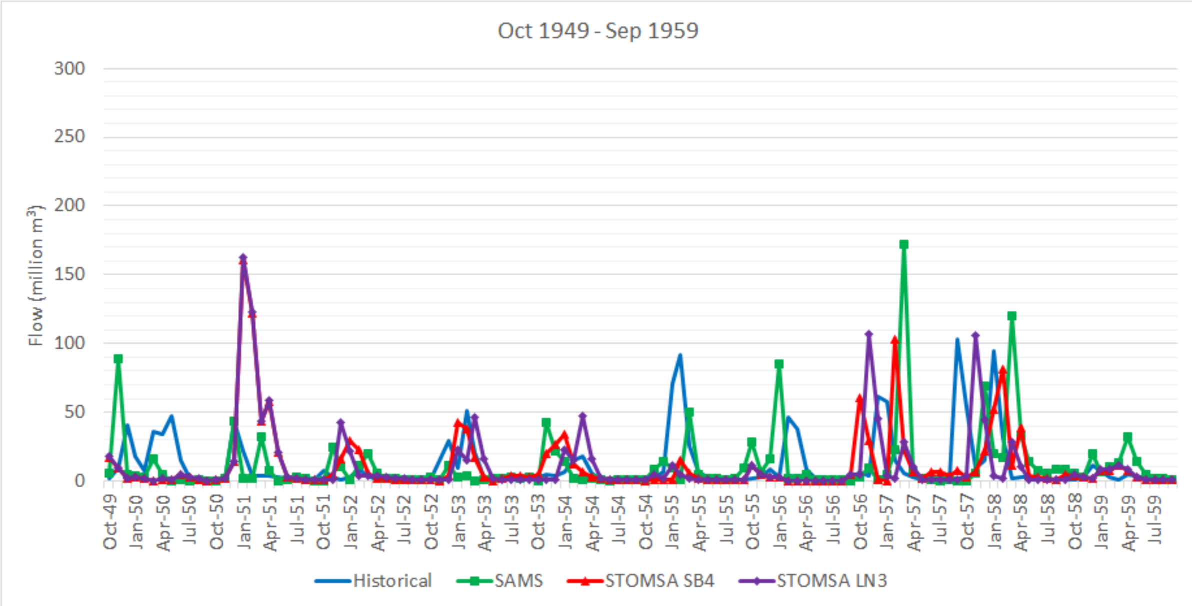

Figure 4.9: Generated stochastic streamflow sequence 11 with STOMSA SB4, STOMSA LN3 and SAMS LN3 marginal distributions, and historical streamflow sequence

Table 4.7: Statistical parameters of five selected stochastic sequences generated using STOMSA with an SB4 marginal distribution, and historical sequence

	Historical	Sequence 11	Sequence 28	Sequence 40	Sequence 63	Sequence 85
Mean	153.69	153.78	168.64	157.94	157.35	142.74
Median	108.31	108.08	95.40	104.59	111.94	110.96
Standard Deviation	141.19	136.60	159.25	137.32	143.90	110.30
Skewness	1.79	1.86	1.33	1.36	1.93	1.17
Minimum	24.98	25.27	25.07	25.46	26.16	27.35
Maximum	658.44	722.20	682.91	601.98	680.03	502.98

From Figure 4.9 and Appendix C.4 it is clear that the stochastic sequences generated using STOMSA with an SB4 marginal distribution have no significant outliers, as opposed to the stochastic sequences generated using SAMS. When the statistical parameters in Table 4.7 are considered a definite correlation between the historical streamflow sequence and the streamflow sequences generated using STOMSA with an SB4 marginal distribution is present.

The average annual streamflow for each sequence was calculated, as discussed in Section 4.4.3, for the stochastic sequences generated using STOMSA with a SB4 marginal distribution. The average annual streamflows of the historical sequence, SAMS and STOMSA LN3 are presented in Figure 4.10 and the statistical parameters are available in Table 4.8.

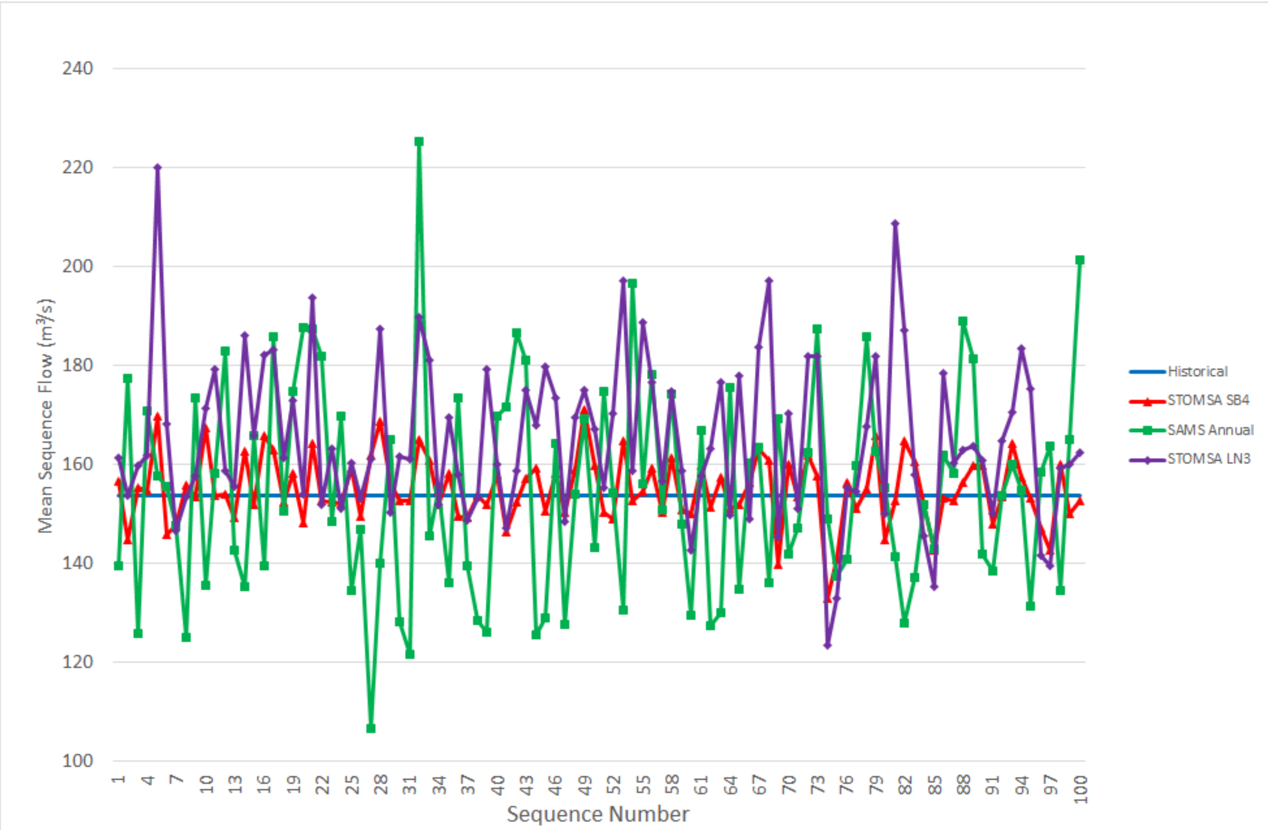

Figure 4.10: Average annual flow per sequence

Table 4.8: Statistical parameters of the average annual generated stochastic streamflows

	SAMS	STOMSA LN3	STOMSA SB4
Mean	155.00	165.04	154.97
Standard Error	2.12	1.61	0.67
Median	154.51	161.57	153.79
Standard Deviation	21.18	16.11	6.75
Sample Variance	448.46	259.46	45.51
Skewness	0.43	0.53	-0.14
Minimum	106.68	123.66	132.93
Maximum	225.24	219.92	171.03

From Figure 4.10 it is clear that the average annual streamflows of the stochastic sequences generated using STOMSA with a SB4 marginal distribution, vary the least. This is supported by the standard error, standard deviation and sample variance presented in Table 4.8. This indicates that the average annual streamflows of the stochastic sequences generated using STOMSA with a SB4 marginal distribution correlate the best with the average annual streamflow of the historical sequence which is 153.69 million m^3/a. The standard deviation as well as the sample variance indicated that the sequences generated by STOMSA with a SB4 marginal distribution has a more consistent average annual flow for each sequence, and is more acceptable.

4.5 Practicality of the SAMS and STOMSA

After both generators were used to generate stochastic streamflow sequences, it was possible to compare the generators in terms of their practicality and ease of use. The comparison of the practicality of the two generators is presented in Table 4.9.

Table 4.9: Practicality comparison of SAMS and STOMSA

	SAMS	STOMSA
Data format	Data has to be in a specific format. Can only handel certain units.	Data has to be in a specific format. Can only handel certain units.
Model setup	Easy to set up with only the assistans of the user manual	Easy to set up with only the assistans of the user manual
Marginal Distirbutions	Very limited in its selection of marginal distributions. Has to mannual transform data to a normal distribution.	Has a sufficient range of marginal distributions and automatically transforms data to a normal distribution.
Time-series distributions	Has a sufficient range of time-series distributions.	Has a sufficient range of time-series distributions.
Stochastic streamflow generation	Able to generate an unlimited amount of stochastic streamflow sequences.	Able to generate only 501 stochastic streamflow sequences.
Results	Presents all the generated stochastic sequences in a single file.	Each stochastic sequences is presented in its own file.
Graphical representation of results	Has a good graphical representation of all the results.	Has a good graphical representation of all the results.

From Table 4.9 it was established that there is not a big difference in the practicality of the two generators. Both generators are easy to set up and use with only the assistance of the user manual of each generator. The only real difference is that SAMS is able to generate an unlimited number of stochastic sequences as opposed to STOMSA that can only generate 100 sequences with an older model, but newer versions have been upgraded to generate up to 501 stochastic sequences.

4.6 Summary

From all the data collected, analysed and compared, it was possible to obtain a good perspective of which model is the best to use under the prescribed circumstances.

From the box and whisker plots, Figures 4.4, 4.5 and 4.8, it was clear that the stochastic streamflows generated by each model are valid. These three figures, however, revealed that the stochastic streamflows generated by SAMS possess an exceptionally high monthly variance.

The comparison using the five randomly selected generated stochastic sequences proved to be an acceptable manner in which to compare the models with the historical data. From Figure 4.6 and Appendix C.3 it was seen that SAMS had big outliers that indicate a high variance of streamflow. Table 4.5 revealed that there was no clear correlation between the stochastic streamflows generated using the SAMS and STOMSA model with an LN3 marginal distribution, and the historical streamflows.

Finally, the analysis using the average annual streamflow of each generated sequence revealed a very high variation in the generated sequences of the SAMS model. The average annual streamflows of the stochastic sequences generated using STOMSA with an LN3 marginal distribution did not vary as much as that of the SAMS model, but a high variance in average annual streamflows was also present.

A third set of stochastic sequences was generated using STOMSA with an SB4 marginal distribution, as discussed in Section 4.3.1. The generated sequences were compared to the historical streamflow sequences, as well as the sequences generated using SAMS and STOMSA with an LN3 marginal distribution, as discussed in Section 4.4.4. From the comparisons it was evident that the stochastic sequences generated using STOMSA with an SB4 marginal distribution correlate the best with the historical streamflow sequence.

With all three comparisons considered it was determined that both SAMS and STOMSA are good stochastic streamflow generators even if some of the generated data did not correlate with that of the historical streamflows. It was, however, evident that the STOMSA generator with an SB4 marginal distribution, generated the most acceptable stochastic sequences. The key evidence is the average annual streamflows presented in Figure 4.10 as well as the statistical parameters in Table 4.5. This indicates the low variance of the average annual streamflows of the stochastic sequences generated using STOMSA with an SB4 marginal distribution by means of the low standard deviation and sample variance. All the sequences were compared in the average annual analysis and provided the same results as that of the analyses using five random sequences.

There is, however, no explanation for the high variations of the stochastic sequences generated using SAMS. It should be considered that SAMS is a product developed in America and the historical streamflow sequence used for the generation of stochastic sequences is one from South Africa. It could be that SAMS overcompensates for the variation in streamflow and therefore produces even bigger variations. Further studies would, however, be necessary to obtain a definite conclusion.

With all the available data from the analyses it was decided that STOMSA would be used with the marginal distribution and time-series distribution it deems best for further analyses in this research.

Chapter 5

WRYM Analyses

In this Chapter Network 1 and Network 2 (Section 3.3) were analysed using the WRYM (Section 2.7). The analyses were done using the methods described in Section 3.4.

Network 1 was analysed first without any evaporation and precipitation on the reservoir surface and after that Network 2 was analysed with evaporation and precipitation on the reservoir surface.

5.1 Stochastic Analyses of Network 1

Network 1 was setup in the WRYM and a historical and stochastic yield analysis were done.

5.1.1 Historical Yield Analysis

The first part of the historical yield analysis was to determine the historical firm yield of the reservoir. This was done using the built in historical firm yield calculator of the WRYM.

In order for the WRYM to calculate the historical firm yield of a given hydrological network, two annual target drafts have to be specified.

The two annual target drafts specified for the calculation of the historical firm yield were 0 million m^3 and 10 million m^3. The iterations used by the WRYM to calculate the historical firm yield and the results are available in Table 5.1.

Table 5.1: WRYM historical firm yield estimation

Iteration	Target Draft (million m^3)	Result
1	0.00	No Failure
2	10.00	Failure
3	5.00	No Failure
4	7.50	Failure
5	6.25	Failure
6	5.62	Failure
7	5.31	Failure
8	5.15	Failure
9	5.07	No Failure
10	5.11	Failure

From Table 5.1 it is seen that the WRYM calculated the historical firm yield to be 5.07 million m^3. This calculated historical firm yield is also graphically presented in Figure 5.1.

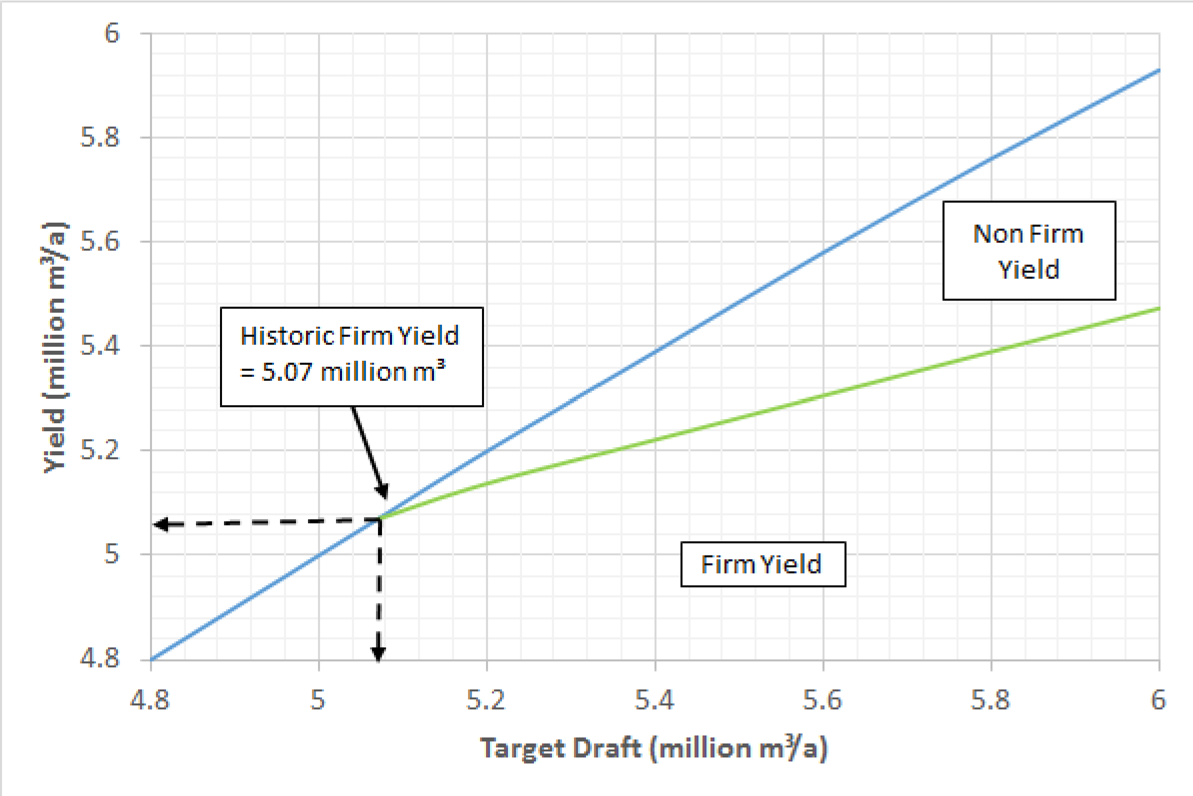

Figure 5.1: Target draft vs yield for Network 1

5.1.2 Stochastic Streamflow Generation

After the historical firm yield was calculated for the network, a stochastic analysis was done. This analysis required the generation of stochastic sequences. A long-term stochastic analysis was done and 201 stochastic streamflow sequences with a length of 35 years were generated.

The WRYM generated the 201 stochastic streamflow sequences using the provided parameter file (Section 3.4.2.1) along with a 2-parameter log-normal marginal distribution and an ARMA (0,1) time-series distribution, which is the most efficient distribution estimated by STOMSA to transform the historical streamflows into a normal distribution.

5.1.3 Riliability of Supply from the WRYM

The 201 stochastic streamflow sequences were generated and a reliability of supply analysis of the network was done. The analysis was done using a single target draft equal to the historical firm yield (5.07 million m^3).

The WRYM calculates the long-term risk of failure and and long-term reliability of supply internally along with the recurrence interval of failures (Section 2.7.3). The model calculated that 19 of the 201 stochastic sequences failed to supply the specified annual target draft. The

WRYM calculated the long-term risk of failure, long-term reliability of supply and the recurrence interval of failures using Equations 2.12, 2.13 and 2.14 from Section 2.7.3 and the results are presented in Table 5.2.

Table 5.2: Results of the risk of failure, reliability of supply and recurrence interval of failures calculated by the WRYM with a target draft of 5.07 *million* m^3

	Results
Risk of Failure	9.95%
Reliability of Supply	90.05%
Recurrence Interval	334 years

The WRYM used the results from Table 5.2 to create a yield-reliability curve for the network with an annual target draft of 5.07 million m^3. This graph is presented in Figure 5.2.

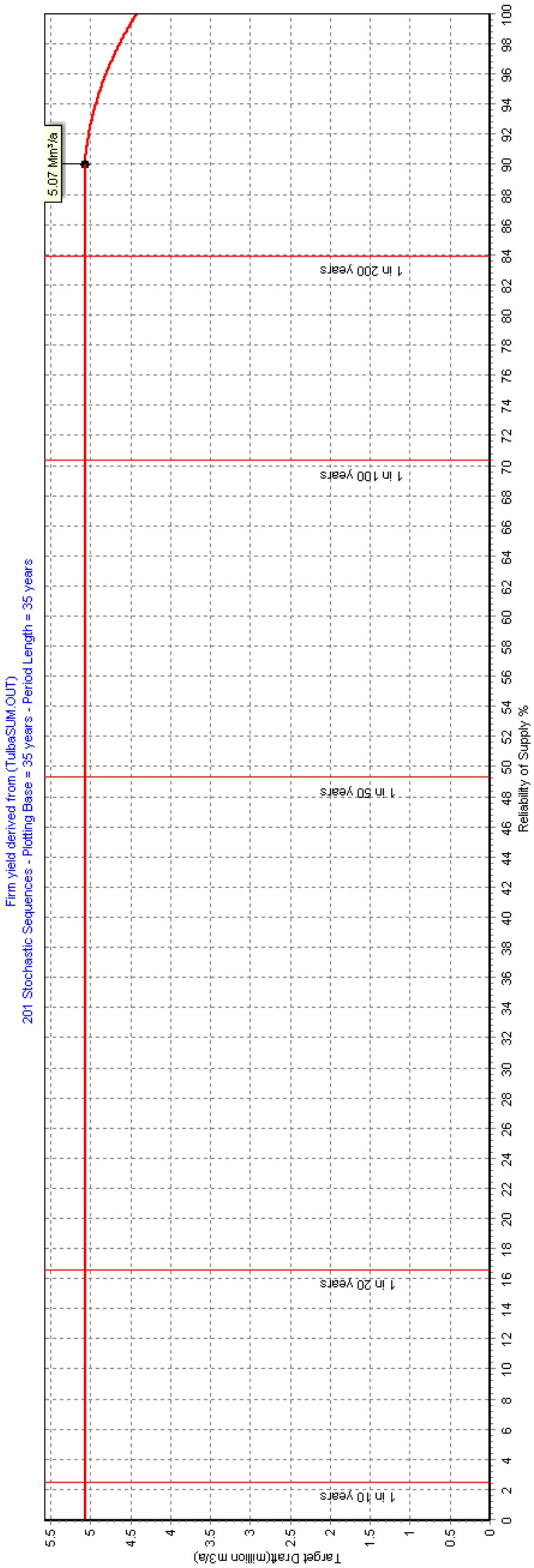

Figure 5.2: Yield-reliability curve from the WRYM

Through inspection of the output files of the WRYM it was found that the WRYM does not take all the failed stochastic sequences into account when calculating the long-term risk of failure and long-term reliability of supply. It was assumed at this stage that the WRYM only calculates a stochastic sequence to be a failure if more than one year within that sequence fails to supply the specified target draft. Evidence of this is available in Appendix F.1. This method of calculating the number of failed sequences is wrong because, as discussed in Section 2.3.2, a stochastic sequence is considered a failed sequence if it fails at least once to supply the specified target draft.

5.1.4 Reliability of Supply Manual Calculations

With the identification of the possible calculation errors made by the WRYM, the output data from the WRYM were analysed manually. The manual stochastic analysis required the generated stochastic streamflow sequences to be abstracted from the output file.

5.1.4.1 Streamflow Conversion

In the WRYM all the inflow and outflow values are converted to cubic meters per second. Therefore, each one of the stochastic sequences was presented as a monthly runoff file that provides water to the reservoir in the output file, with values in cubic meters per second. Each one of the stochastic streamflow files had to be converted to streamflow files containing values in million cubic meters for each month. The process used by the WRYM to convert the streamflow values, with the main concern being how the model handles leap years, had to be determined in order to reverse the process.

The best way to find out how the model converts the streamflows was to take the historical streamflow file and determine how the file was converted from million cubic meters for each month into cubic meters per second. It was established that the WRYM uses Equation 5.1 to convert the monthly streamflows into cubic meters per second.

$$Streamflow\ (m^3/s) = \frac{Streamflow\ (million\ m^3/month)}{60(sec) \times 60(min) \times 24(h) \times days\ in\ month} \times 1\ 000\ 000 \qquad (5.1)$$

Equation 5.1 worked very well for every month, with the exception being February. February does not have a constant number of days and every fourth year (leap year) it has an extra day. Equation 5.1 was tested using the streamflow of February 1969, recorded in the historical streamflow file, to determine if the equation provides the same answer as the WRYM. In the WRMF Version 4.3.0.0 it is indicated that the model uses a constant 28.5 days for February in the conversion process in order to take the leap years into account. The calculation is available in Equation 5.2.

$$\begin{aligned} February\ Streamflow\ (m^3/s) &= \frac{0.28}{60 \times 60 \times 24 \times 28.5} \times 1\ 000\ 000 \\ &= 0.11371\ m^3/s \end{aligned} \tag{5.2}$$

The answer from Equation 5.2 (0.11371 m^3) does not match the answer obtained from the WRYM (0.1147 m^3). The WRYM, therefore, does not use a constant of 28.5 days when for the conversion of streamflows for February. The WRYM rather uses an average value over four years. When the WRYM converts streamflows for February it converts the streamflow to cubic meters per second, using 28 days and times the converted answer by three. The model then converts the streamflow again using 29 days. The two converted answers are added together and divided by four to obtain an average monthly streamflow in cubic meters per second for February. The WRYM uses this procedure in order to take the leap years into account. The conversion process for February streamflows is illustrated in Equations 5.3, 5.4 and 5.5.

February streamflow conversion for 28 days:

$$February\ Streamflow\ (m^3/s) = 3 \times \left(\frac{Streamflow\ (million\ m^3/month)}{60(sec) \times 60(min) \times 24(h) \times 28(days)} \right) \times 1\ 000\ 000 \tag{5.3}$$

February streamflow conversion for 29 days:

$$February\ Streamflow\ (m^3/s) = \frac{Streamflow\ (million\ m^3/month)}{60(sec) \times 60(min) \times 24(h) \times 29(days)} \times 1\ 000\ 000 \tag{5.4}$$

Average of February streamflow conversions:

$$February\ Streamflow\ (m^3/s) = \frac{28\ day\ flow(m^3/s) + 29\ day\ flow(m^3/s)}{4} \tag{5.5}$$

When Equations 5.3, 5.4 and 5.5 were applied to February 1969 and the converted streamflow was calculated to be 0.1147 m^3. The calculation is illustrated in Equation 5.6

$$\begin{aligned}February\ Streamflow\ (m^3/s) &= \left(\frac{0.28 \times 3}{60 \times 60 \times 24 \times (28)} + \frac{0.28}{60 \times 60 \times 24 \times 29}\right) \times \frac{1\ 000\ 000}{4} \\ &= 0.1147 m^3/s\end{aligned} \tag{5.6}$$

Once the process used by the WRYM to convert streamflows from million cubic meters for each month to cubic metres per second was determined, the process was reversed to convert the outflow data values through the yield channel from the WRYM to outflows in million cubic meters.

5.1.4.2 Calculated Long-term Reliability of Supply

After the conversion of the stochastic outflows, the base yield (Section 2.3.1) was calculated for each stochastic sequence in order to determine the long-term risk of failure and long-term reliability of supply. The base yields were sorted from high to low and given a rank number form 1 to 201, with 1 being the highest base yield. Each rank number was then calculated as a percentage of the total number of stochastic sequences (201) to determine a plotting position for the base yield. An extract of the base yields along with their ranking position are available in Appendix G.1. The ranked base yields are graphically presented in Figure 5.3.

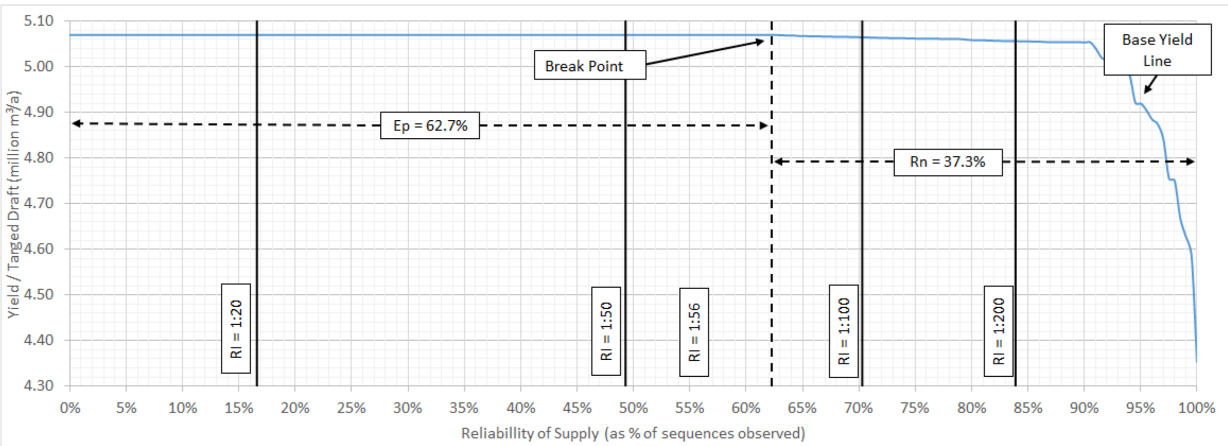

Figure 5.3: Yield-reliability curve of the WRYM without gains and losses

It was calculated that 75 of the 201 stochastic sequences had base yields smaller than the specified annual target draft of 5.07 million m^3. Therefore a total of 75 stochastic sequences failed to provide the specified annual target draft. With the number of failed sequences known, the long-term risk of failure and long-term reliability of supply as well as the recurrence interval of failures were calculated using Equations 2.12, 2.13 and 2.14 from Section 2.7.3. The results of the calculations are available in Table 5.3 and also graphically presented in Figure 5.3.

Table 5.3: Results of the manually calculated risk of failure, reliability of supply and recurrence interval of failures.

	Results
Risk of Failure	37.81%
Reliability of Supply	62.19%
Recurrence Interval	75 years

5.1.5 Comparison of the WRYM and Manual Calculations

After the long-term risk of failure, reliability of supply and the recurrence interval of failures were calculated manually from the output file of the WRYM, the answers were compared to those calculated by the WRYM. The answers are summarised in Table 5.4.

Table 5.4: Comparison of results of the WRYM and manual calculations for a network without gains and losses

	WRYM	Manual Calculations
Risk of Failure	9.95%	37.81%
Reliability of Supply	90.05%	62.19%
Recurrence Interval	334 years	75 years

From Table 5.4 it is presented that the WRYM makes an possible calculation error in the determination of the number of failed stochastic sequences. The possible calculation error has a great impact on the results. The WRYM calculates Network 1 to be more than 30% more reliable than the network actually is. Furthermore the recurrence interval of failures calculated by the WRYM is more than 4 times longer than calculated manually.

5.2 Stochastic Analyses of Network 2

Network 2 was set up in the WRYM and a historical and stochastic yield analysis were done.

5.2.1 Evaporation

The WRYM requires a monthly evaporation distribution in millimeters in order to analyse the network while taking evaporation from the reservoir surface into account. The evaporation distribution calculated in Section 3.3.6 was imported into the WRYM for this analysis.

The WRYM uses the monthly evaporation distribution to calculate the rate of evaporation from the reservoir surface for each month of an analysis. The evaporation for a given month in an analysis is calculated by multiplying the distributed evaporation for that month with the reservoir surface area at the beginning of each month. An example of the calculation of evaporation for October 1968 of stochastic sequence 1, is available in Equation 5.7 and the calculated evaporation from the reservoir surface for each month by the WRYM of stochastic sequence 1 is available in Appendix J.1.

$$\begin{aligned} Evap\ October\ (m^3/s) &= \frac{Evap\ Distribution\ October(mm) \times Reservoir\ Surface\ Area(m^2)}{60(sec) \times 60(min) \times 24(hours) \times 31(days)} \\ &= \frac{113.796 \times 2\ 600\ 00}{60 \times 60 \times 24 \times 31} \\ &= 0.01105\ m^3/s \end{aligned} \tag{5.7}$$

5.2.2 Precipitation

The WRYM requires a monthly historical rainfall input file in order to take precipitation on the reservoir surface into account. The rainfall file created in section 3.3.7 was imported into the WRYM for the analysis.

The WRYM uses the monthly historical rainfall input file to calculate the total precipitation on the reservoir surface for each month of an analysis. For the historical yield analysis the WRYM used the created historical rainfall file and multiplied the monthly precipitation with the reservoir surface area at the beginning of that month to determine the volume of precipitation on the reservoir surface for that month.

For the stochastic yield analysis the WRYM first had to calculate the streamflow, for each month of a stochastic streamflow sequence, as a fraction of the historical MAR (14.847 million m^3) and then multiply the fraction with the MAP (475mm) to obtain a stochastic precipitation for that month. The rate of precipitation on the reservoir surface for each month of each stochastic streamflow sequence was calculated by multiplying the stochastic precipitation for that month with the reservoir surface area at the beginning of that month. An example of the calculation of precipitation for October 1968 of stochastic sequence 1 is available in Equations 5.8 and 5.9. The calculated precipitation for each month by the WRYM of stochastic sequence 1 is available in Appendix J.2.

Precipitation for October 1968

$$\begin{aligned} Rainfall\ October\ (mm) &= \frac{Month\ Streamflow}{MAR} \times MAP \\ &= \frac{1.28}{14.847} \times 475 \\ &= 40.959\ mm \end{aligned} \tag{5.8}$$

Rate of precipitation for October 1968

$$\begin{aligned} Rainfall\ October\ (m^3/s) &= \frac{Precipitation(mm) \times Reservoir\ Surface\ Area(m^2)}{60(sec) \times 60(min) \times 24(hours) \times 31(days)} \\ &= \frac{40.959 \times 2\ 600\ 00}{60 \times 60 \times 24 \times 31} \\ &= 0.00398\ m^3/s \end{aligned} \tag{5.9}$$

5.2.3 Historical Yield Analysis

The historical yield analysis for Netwrok 2 was done using the same procedure described in Section 5.1.1.

The same two annual target drafts used for the calculation of the historical firm yield of Network 1 (0 million m^3 and 10 million m^3) were used for the calculation of the historical firm yield of Network 2. The iterations used by the WRYM to calculate the historical firm yield and the results are available in Table 5.5.

Table 5.5: WRYM historical firm yield estimation

Iteration	Target Draft (million m^3)	Result
1	0	No Failure
2	10	Failure
3	5	Failure
4	2.5	No Failure
5	3.75	No Failure
6	4.37	No Failure
7	4.68	No Failure
8	4.84	Failure
9	4.78	No Failure
10	4.8	Failure

From Table 5.5 it is seen that the WRYM calculated the historical firm yield to be 4.78 million m^3. The calculated historical firm yield is also graphically presented in Figure 5.4.

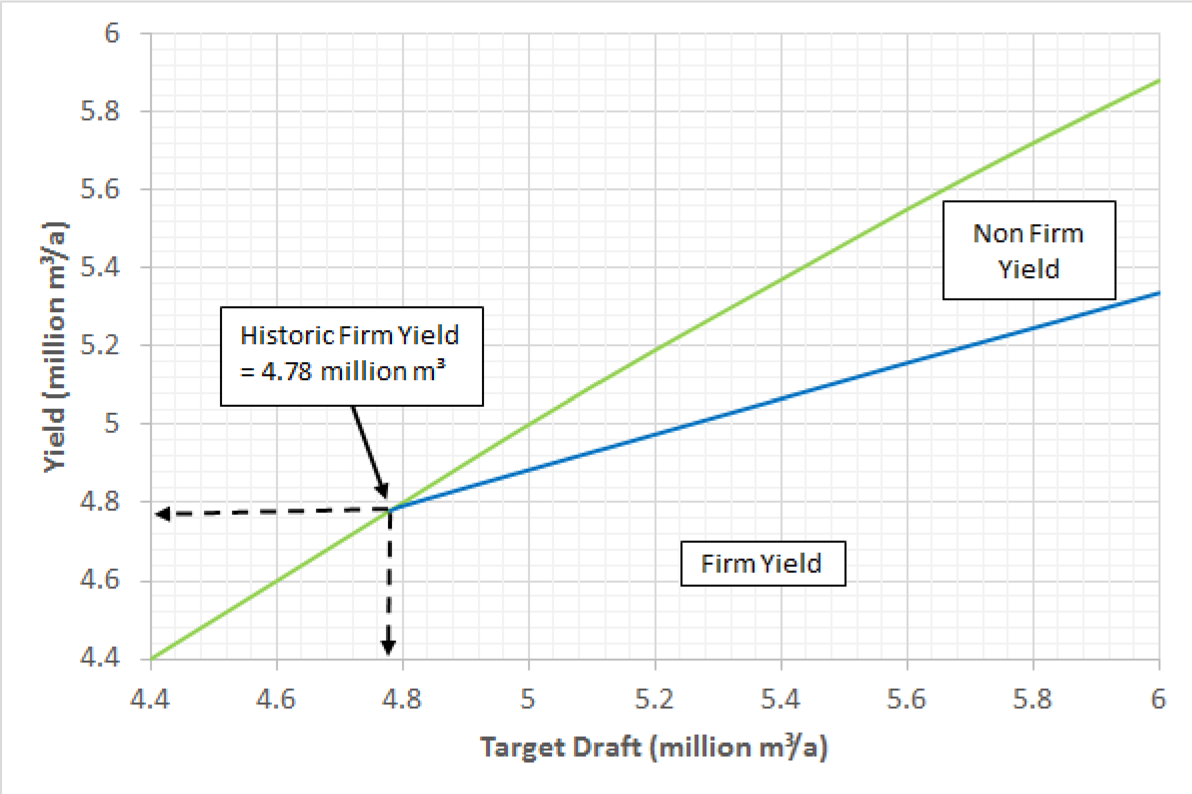

Figure 5.4: Target draft vs yield for Network 2

5.2.4 Stochastic Streamflow Generation

A stochastic analysis was done for Netwrok 2 using the same procedure described in Section 5.1.2.

5.2.5 Reliability of Supply from the WRYM

The 201 stochastic streamflow sequences were generated, and a reliability of supply analysis of the network was done. The analysis was done using a single target draft equal to the historical firm yield (4.78 million m^3).

In Section 5.1.3 it was stated that the WRYM calculates the long-term risk of failure and long-term reliability of supply internally along with the recurrence interval of failures. It was, however, determined that the model makes a possible calculation error when it determines the amount of failed stochastic sequences. The same problem that occurred in Section 5.1.3 observed again in this analysis.

The WRYM determined that a total of 30 stochastic sequences failed to supply the specified annual target draft, when there were actually 95 stochastic sequences that failed. This time, however, it was found that the WRYM does not accept a stochastic sequence to be a failure if more than one year within that sequence fails to supply the specified target draft as what was assumed in Section 5.1.3. It was found that 35 of the generated stochastic sequences contained more than one year that failed to supply the specified annual target draft, but the WRYM accepted a value of 30 without any further indication of where this number of failures had been obtained from. Evidence of this is presented in Appendix F.2.

The results of the long-term risk of failure, long-term reliability of supply and the recurrence interval of failures calculated by the WRYM are available in Table 5.6.

Table 5.6: Results of the risk of failure, reliability of supply and recurrence interval of failures calculated by the WRYM with gains and losses.

	Results
Risk of Failure	15.42%
Reliability of Supply	84.58%
Recurrence Interval	209 years

5.2.6 Reliability of Supply Manual Calculations

With the identification of the possible calculation errors made by the WRYM, the output data from the WRYM for Network 2 were analysed manually.

The outflow data had to be converted form cubic meters per second to million cubic meters, using the same conversion process described in Section 5.1.4. After the conversion of the outflow data, the base yield was calculated and ranked for each stochastic sequence in order to determine the long-term risk of failure and long-term reliability of supply of the network. An extract of the base yields along with their ranking position are available in Appendix G.2. The ranked base yields were used to set up a yield-reliability curve presented in Figure 5.5.

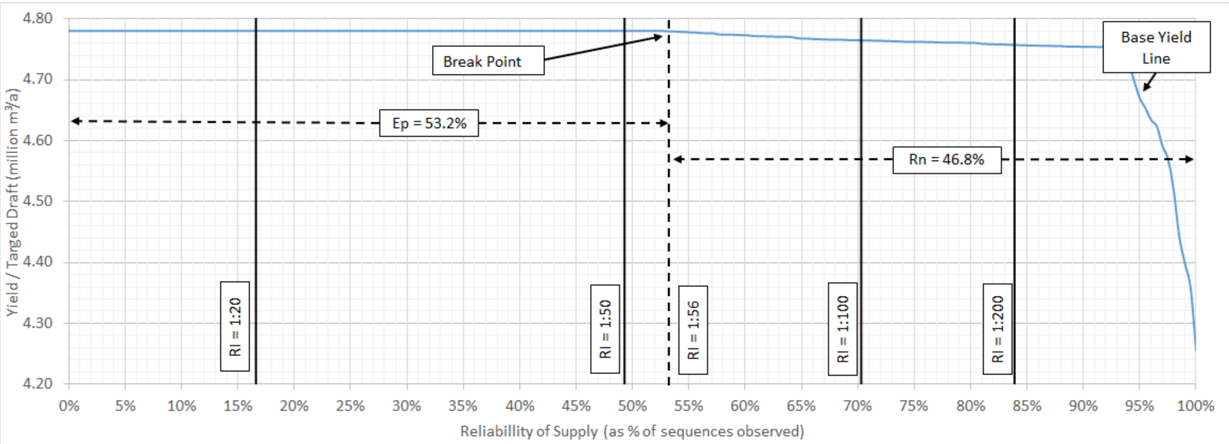

Figure 5.5: Yield-reliability curve of the WRYM with gains and losses

It was calculated that 95 of the 201 stochastic sequences had base yields smaller than the specified annual target draft of 4.78 million m^3. Therefore a total of 95 stochastic sequences failed to provide the specified annual target draft. With the number of failed sequences known, the long-term risk of failure and reliability of supply, as well as the recurrence interval of failures, were calculated. The results are presented in Table 5.7 and also graphically presented in Figure 5.5.

Table 5.7: Manually calculated risk of failure, reliability of supply and recurrence interval of failures.

	Results
Risk of Failure	47.30%
Reliability of Supply	52.70%
Recurrence Interval	55 years

5.2.7 Comparison of the WRYM and Manual Calculations

After the long-term risk of failure, reliability of supply and the recurrence interval of failures were calculated manually from the output file of the WRYM, these answers could be compared to those calculated by the WRYM. These answers are summarised in Table 5.8.

Table 5.8: Comparison of results of the WRYM and manual calculations for Network 2 with gains and losses

	WRYM	Manual Calculations
Risk of Failure	15.42%	47.30%
Reliability of Supply	84.58%	52.70%
Recurrence Interval	209.45 years	55 years

From Table 5.8 it is evident that the same possible calculation error was made by the WRYM, that was presented in Section 5.1.5, in the determination of the number of failed stochastic sequences for Network 2. It is presented that the WRYM calculates the network to be more than 30% more reliable than the network actually is. Furthermore the recurrence interval of failures calculated by the WRYM is nearly 4 times longer than that calculated manually.

5.3 Additional Stochastic Analyses

In Sections 5.1 and 5.2 it was established that the WRYM makes a possible calculation error whenever the model determines the number of failed stochastic sequences. In order to determine if the model does make a calculation error additional analyses were done. The additional analyses were done using an older version of the WRYM (WRIMS 3.8.2) as well as a new historical streamflow file (C9R002 from Bloemhof dam).

5.3.1 WRIMS Version 3.8.2

WRIMS Version 3.8.2 is an older version of the WRMF that was used for the original analyses. WRIMS 3.8.2 was used for an additional stochastic analysis of Network 1 to determine if the identified possible calculation error made by the WRYM is only restricted to the new version of the WRYM in the WRMF Version 4.3.0.0.

Network 1 was set up in WRIMS 3.8.2 for an additional stochastic analysis. The same historical data that was used in the original analysis in Sections 5.1 was used for this analysis. WRIMS 3.8.2, however, presented the same results for Network 1 as the WRMF 4.3.0.0 in Section 5.1.3. The model determined that 19 of the 201 stochastic sequences failed to supply the specified annual target draft of 5.07 million m^3, while there were in fact 75 stochastic sequences that failed to supply the annual target draft.

The analysis with WRIMS 3.8.2 therefore confirmed that the possible calculation error made by the WRYM is not restricted to the WRMF 4.3.0.0.

5.3.2 Additional Historical Data

An additional historical streamflow file was used for further analyses of Network 1 to determine if there was a problem with the data from flow station G1R001. Network 1 was set up in the WRYM using the same process described in Chapter 3. The only alteration made to the network was the historical flow sequence that was used as inflow to the reservoir. The historical flow sequence from flow station C9R002 at Bloemhof dam was used in the analysis instead of the historical flow sequence from flow station G1R001 at Voëlvlei dam. The historical flow sequence from flow station C9R002 was used for the additional analysis as it was already used for the comparison of STOMSA and SAMS in Chapter 4 and did not produce any problems.

A historical yield analysis was done for Network 1 and it was determined that the historical firm yield is 2.50 million m^3/a for the historical data from flow station C9R002.

A stochastic yield analysis was also done for the network with the annual target draft equal to the historical firm yield of 2.50 million m^3/a. 201 stochastic streamflow sequences were generated within the WRYM and analysed. The long-term risk of failure, long-term reliability of supply and the recurrence interval of failures were calculated by the WRYM. The WRYM determined that zero of the 201 stochastic sequences failed to supply the specified annual target draft and therefore the network is 100% reliable. The record of sequence failures in the output file of the WRYM, however, presented that 53 of the stochastic sequences failed to provide the specified annual target draft.

A manual stochastic yield analysis was done for Network 1, using the 201 stochastic streamflow sequences generated from the historical streamflows of flow station C9R002. The historical firm yield of 2.50 million m^3/a was used a the target draft and the long-term reliability of supply was calculated using the same procedure described in Section 5.1.4.2. From the manual calculations it was determined that a total of 53 stochastic sequences failed to supply the specified annual target draft and that the network was only 74% reliable. The results of the manual calculation therefore again contradicts the results of the WRYM.

The monthly reservoir volume of stochastic streamflow sequence 7 was analysed for the WRYM and the manual calculations. Sequence 7 was the fist sequence to present a failure in both the WRYM and the manual calculations. The monthly reservoir volumes of both models are graphically presented in Figures 5.6 and 5.7.

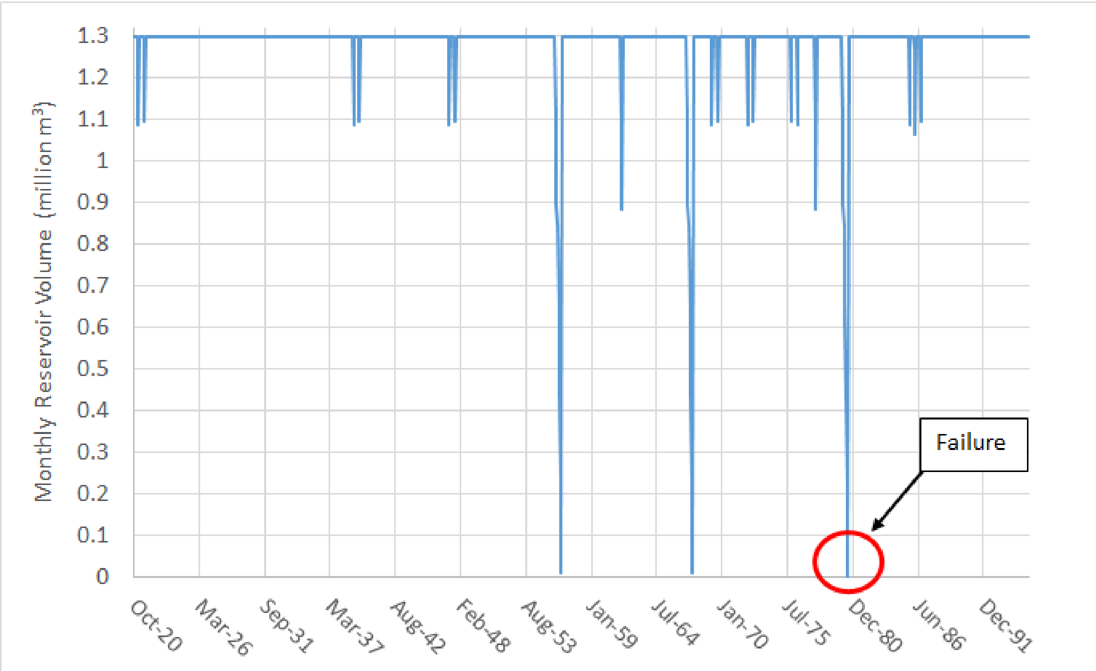

Figure 5.6: Monthly reservoir volume of stochastic sequence 7 analysed by the WRYM

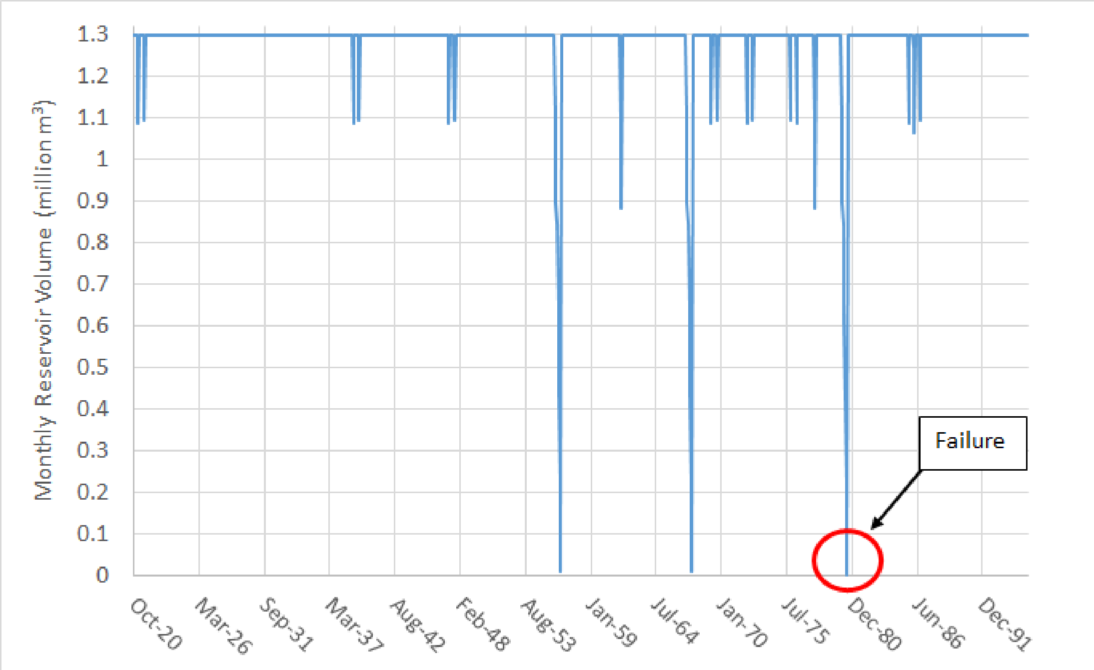

Figure 5.7: Monthly reservoir volume of stochastic sequence 7 manually analysed

From Figures 5.6 and 5.7 it is clear that the WRYM and the manual calculations present the same results and that stochastic sequence 7 contains one failure. The WRYM, however, fails to count this failure and instead states that zero stochastic sequences failed for the analysis.

Further stochastic analyses were done with the WRYM as well as the manual model for Network 1, using target drafts higher than the historical firm yield. From the analyses it was determined that with annual target drafts much higher than the historical firm yield, the WRYM does not make the calculation error and the number of failed stochastic sequences calculated by the WRYM is the same as the failed stochastic sequences calculated manually. However, when the annual target draft gets close to the historical firm yield, the WRYM calculates that fewer stochastic sequences fail to supply the specified annual target draft than the manual model. Table 5.9 provides a summary of different annual target drafts and the number of sequence failures calculated by the WRYM as well as manually.

Table 5.9: Sequence failures for different target drafts

Target Draft (million m^3/a)	Number of failed sequences: WRYM	Number of failed sequences: Manual Calculations
2.50	0	53
2.51	0	147
2.52	57	151
2.53	122	151
2.54	151	151
2.55	151	151

From Table 5.9 it is clear that the WRYM is more conservative in the calculation of the number of failed stochastic sequences when the annual target draft is close to the historical firm yield.

5.3.3 Data and Network Validation

The WRYM allows the user to validate the input data of an analysis as well as the network used for the analysis. Both Network 1 and Network 2 were validated by the WRYM and the model did not find any problems with the two networks. Both set of historical data from flow station G1R001 and C9R002 were also validated by the WRYM and were found to be valid data.

5.4 Summary

In this chapter two hydrological networks were analysed with the WRYM; one network taking evaporation and precipitation on the reservoir surface into consideration and the one without the impact of evaporation and precipitation. A historical as well as a stochastic yield analysis was done for both networks. For each network 201 stochastic streamflows were generated, using the STOMSA stochastic streamflow generator, and used to calculate the long-term reliability of supply. From the analyses it was determined that the WRYM overestimates the assurance of supply if compared with a manual calculation of the long-term reliability of supply. An evaluation of the calculation procedure used by the WRYM revealed that a possible calculation error was made by the WRYM. The possible error was in the calculation of the number of failed sequences, where in both analyses the number of failed sequences calculated by the WRYM was far less than the actual number of failed sequences. The results from the analyses are summarised in Table 5.10.

Table 5.10: Summary of results of the WRYM and manual calculations

	Network 1		Network 2	
	WRYM	Mannual	WRYM	Mannual
Risk of Failure	9.95%	37.81%	15.42%	47.30%
Reliablility of Supply	90.05%	62.19%	84.58%	52.70%
Recurrence Interval	334 years	75 years	209 years	55 years

Additional analyses were done for Network 1 to determine if the calculation problem of the WRYM is restricted to the latest version of the WRYM and if the data that was used in the analysis was valid. From the analyses is was clear that the older version of the WRYM (WRIMS 3.8.2) makes the same calculation error as the latest version of the WRYM (WRMF 4.3.0.0). An additional set of data was used for further analyses (C2R009) and also resulted in contradicting answers between the WRYM and the manual calculations. It was established that in the case where the specified annual target draft is much higher than the historical firm yield, the WRYM presents the correct number of failed stochastic sequences that matches the number calculated manually. However, when the specified annual target draft is close to the historical firm yield, the WRYM is very conservative in the calculation of the number of failed stochastic sequences.

In Chapte 6 the generated stochastic sequences from the analyses were used for further analyses using the MIKE Hydro Basin software. The results from this chapter (WRYM) were compared to the results from MIKE Hydro Basin in Chapter 7.

Chapter 6

MIKE Hydro Basin Analyses

In this Chapter Network 1 and Network 2 (Section 3.3) were analysed using MIKE Hydro Basin (Section 2.8). The analyses were done using the methods described in Section 3.5.

Network 1 was analysed first without any evaporation and precipitation on the reservoir surface and after that Network 2 was analysed with evaporation and precipitation on the reservoir surface.

6.1 Historical Yield Analysis of Network 1

The historical yield analysis was done to determine the historical firm yield of the reservoir. This was done by manually increasing the amount of water that is abstracted annually from the reservoir (target draft) until the reservoir reached a capacity of 0 million m^3. An extract of the various annual target drafts, along with the associated minimum reservoir capacity, are presented in Table 6.1.

Table 6.1: MIKE Hydro Basin historical firm yield estimation

Target Draft (million m^3)	Minimum Capacity (million m^3)	Result
5.06	0.024	No Failure
5.07	0.018	No Failure
5.08	0.012	No Failure
5.09	0.006	No Failure
5.10	0.000	Failure

From Table 6.1 it is presented that the estimated historical firm yield for Network 1 in MIKE Hydro Basin is 5.09 million m^3. This is the largest amount of water that can be abstracted annually from the reservoir without the reservoir reaching a capacity of 0 million m^3.

6.2 Stochastic Analyses of Network 1

With Network 1 set up in MIKE Hydro Basin, a stochastic yield analysis wass for the network. For the stochastic yield analyses, the 201 stochastic streamflow sequences generated in the WRYM (Section 5.1.2) were imported into MIKE Hydro Basin as historical streamflow files. Each one of the 201 stochastic sequence files was analysed on its own.

6.2.1 Conversion of the Target Draft

During the stochastic yield analyses the historical firm yield calculated by the WRYM (5.07 million m^3), was used as the annual target draft. MIKE Hydro Basin allows the user to specify the target draft annually in million cubic meters or monthly in cubic meters per second.

When the target draft is specified annually in MIKE Hydro Basin, the model converts the annual target draft to cubic meters per second. It was found that MIKE Hydro Basin does not take leap years into account in the conversion process of the model, and that the model makes use of Equation 6.1 to convert the annual target draft to cubic meters per second.

$$\begin{aligned} Streamflow\ (m^3/s) &= \frac{Streamflow\ (million\ m^3/a)}{60(sec) \times 60(min) \times 24(h) \times 365(days)} \times 1\ 000\ 000 \\ &= \frac{5.07}{60 \times 60 \times 24 \times 365} \times 1\ 000\ 000 \\ &= 0.16077\ m^3/s \end{aligned} \tag{6.1}$$

The conversion process used by MIKE Hydro Basin made it difficult to compare the model to the WRYM, which takes leap years into account in its conversion process. The conversion process used by the WRYM (Section 5.1.4.1) was used to convert the annual target draft into cubic meters per second. The converted target draft was then imported into MIKE Hydro Basin. The conversion of the annual target draft is illustrated in Equations 6.2, 6.3 and 6.4.

Conversion without leap years:

$$\begin{aligned} Streamflow\ (m^3/s) &= 3 \times \frac{Streamflow\ (million\ m^3/a)}{60(sec) \times 60(min) \times 24(h) \times 365(days)} \times 1\ 000\ 000 \\ &= 3 \times \frac{5.07}{60 \times 60 \times 24 \times 365} \times 1\ 000\ 000 \\ &= 0.4823\ m^3/s \end{aligned} \tag{6.2}$$

Conversion with leap year:

$$\begin{aligned} Streamflow\ (m^3/s) &= \frac{Streamflow\ (million\ m^3/a)}{60(sec) \times 60(min) \times 24(h) \times 366(days)} \times 1\ 000\ 000 \\ &= \frac{5.07}{60 \times 60 \times 24 \times 366} \times 1\ 000\ 000 \\ &= 0.16033\ m^3/s \end{aligned} \tag{6.3}$$

Average of conversions:

$$\begin{aligned} February\ Streamflow\ (m^3/s) &= \frac{365\ day\ flow(m^3/s) + 366\ day\ flow(m^3/s)}{4} \\ &= \frac{0.4823 + 0.16033}{4} \\ &= 0.16066\ m^3/s \end{aligned} \tag{6.4}$$

6.2.2 Analysis of Stochastic Streamflow Sequences

With the model set up, each one of the stochastic sequences was imported into the model as a historical streamflow file and analysed separately. During each analysis the monthly outflow through the yield channel for the 35 years was recorded.

The recorded outflows were converted from cubic meters per second to million cubic meters for each month. The same conversion process used for the WRYM (Section 5.1.4.1) was used to convert the outflows. After the conversion was done, the base yield for each sequence was calculated.

6.2.3 Reliability of Supply

With the base yields calculated for each stochastic sequence, it was possible to calculate the long-term risk of failure and long-term reliability of supply as well as the recurrence interval of failures for the network.

The same procedure used for the manual calculations of the WRYM to rank the base yields (Section 5.1.4.2) were used for this analysis. An extract of the base yields, along with their ranking position, is available in Appendix H.1. These ranked base yields were used to set up a yield-reliability curve and is presented in Figure 6.1.

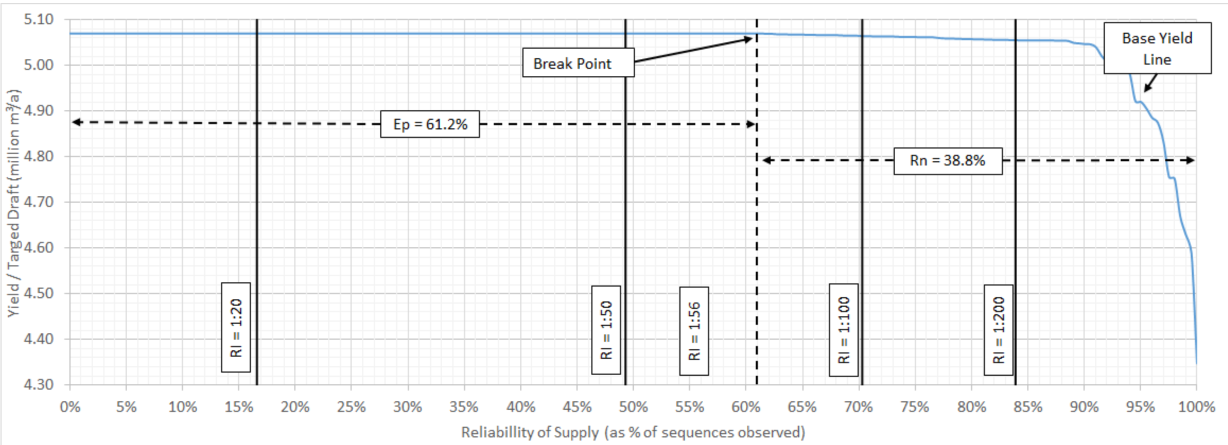

Figure 6.1: Yield-reliability curve for MIKE Hydro Basin without gains and losses

It was calculated that 78 of the 201 stochastic sequences had base yields smaller than the specified annual target draft of 5.07 million m^3. Therefore a total of 78 stochastic sequences failed to provide the specified annual target draft. With the number of failed sequences known, the long-term risk of failure and long-term reliability of supply, as well as the recurrence interval of failures, were calculated using Equations 2.12, 2.13 and 2.14 from Section 2.7.3, the same equations used in the manual calculation of the WRYM. The results of the calculations are available in Table 6.2 and also graphically presented in Figure 6.1.

Table 6.2: Results of the calculated risk of failure, reliability of supply and recurrence interval of failures from MIKE Hydro Basin.

	Results
Risk of Failure	38.80%
Reliability of Supply	61.20%
Recurrence Interval	72 years

6.3 Historical Yield Analysis of Network 2

The historical yield analysis was done for Network 2 using the same procedure as for the historical yield analysis of Network 1 in Section 6.1. An extract of the various annual target drafts along with the associated minimum reservoir capacity is presented in Table 6.3.

Table 6.3: MIKE Hydro Basin historical firm yield estimation

Target Draft (million m^3)	Minimum Capacity (million m^3)	Result
4.76	0.017	No Failure
4.77	0.012	No Failure
4.78	0.006	No Failure
4.79	0.001	No Failure
4.80	0.000	Failure

From Table 6.3 it is clear that the estimated historical firm yield for Network 2 in MIKE Hydro Basin is 4.79 million m^3 and is therefore the largest amount of water that can be abstracted annually from the reservoir without the reservoir reaching a capacity of 0 million m^3.

6.4 Stochastic Analyses of Network 2

With Network 2 set up in MIKE Hydro Basin, a historical and stochastic yield analysis could be done for the network. The stochastic yield analyses for Network 2 was done using the same procedure as for the stochastic yield analysis of Network 1 in Section 6.2.

6.4.1 Evaporation

MIKE Hydro Basin requires a monthly evaporation distribution in millimeters in order to analyse the network while taking evaporation from the reservoir surface into account. The evaporation distribution calculated in Section 3.3.6 was imported into the MIKE Hydro Basin for the stochastic yield analysis.

MIKE Hydro Basin uses the monthly evaporation distribution to calculate the volume of evaporation from the reservoir surface for each month of an analysis. The evaporation for a given month in an analysis is calculated by multiplying the distributed evaporation for that month with the reservoir surface area at that particular stage. An example of the calculation of evaporation for October 1968 of stochastic sequence 1 is available in Equation 6.5 and the calculated evaporation for each month by MIKE Hydro Basin of stochastic sequence 1 is available in Appendix K.1.

$$\begin{aligned} Evap\ October\ (m^3/s) &= \frac{Evap\ Distribution\ October(mm) \times Reservoir\ Surface\ Area(m^2)}{60(sec) \times 60(min) \times 24(hours) \times 31(days)} \\ &= \frac{113.796 \times 2\ 600\ 00}{60 \times 60 \times 24 \times 31} \\ &= 0.01105\ m^3/s \end{aligned} \tag{6.5}$$

6.4.2 Precipitation

MIKE Hydro Basin requires a monthly rainfall input file for each one of the stochastic stream flow sequences in order to take precipitation on the reservoir surface into account. Rainfall files from October 1968 to September 2003 were created for each stochastic streamflow sequence. The rainfall files were created using the calculation process described in Section 3.5.2.2.

An example of the calculation of the precipitation of stochastic streamflow sequence 1 for October 1968 is available in Equation 6.6 and the total calculated stochastic rainfall input file for sequence 1 is available in Appendix I.

$$\begin{aligned} Stochstic\ Month\ Rainfall &= \frac{Month\ Streamflow}{MAR} \times MAP \\ &= \frac{1.28}{14.847} \times 475 \\ &= 40.96\ mm \end{aligned} \tag{6.6}$$

MIKE Hydro Basin uses these stochastic rainfall files to calculate the volume of precipitation on the reservoir surface for each month. The volume of precipitation on the reservoir surface for each month of each stochastic streamflow sequence was calculated by multiplying the stochastic precipitation for that month with the reservoir surface area at the beginning of that month. An example of this calculation of the volume of precipitation on the reservoir surface for October 1968 of stochastic sequence 1 is available in Equations 6.7. The calculated precipitation for each month by MIKE Hydro Basin of stochastic sequence 1 is available in Appendix K.2.

$$
\begin{aligned}
Rainfall\ October\ (m^3/s) &= \frac{Precipitation(mm) \times Reservoir\ Surface\ Area(m^2)}{60(sec) \times 60(min) \times 24(hours) \times 31(days)} \\
&= \frac{40.96 \times 2\ 600\ 00}{60 \times 60 \times 24 \times 31} \\
&= 0.00398\ m^3/s
\end{aligned}
\tag{6.7}
$$

6.4.3 Analysis of Stochastic Streamflow Sequences

With the model set up, each one the 201 stochastic streamflow files, along with created rainfall file and monthly evaporation distribution, were imported into the model and analysed separately. During the stochastic yield analyses the historical firm yield calculated using the WRYM (4.78 million m^3) was used as the annual target draft. The annual target draft was converted into cubic meters per second, using the same conversion process as described in Section 6.2.1. For each analysis the monthly outflow through the yield channel for the 35 years was recorded.

The recorded outflows had to be converted from cubic meters per second to million cubic meters for each month. The same conversion process used for the WRYM (Section 5.1.4.1) was used to convert the outflows and the base yield for each sequence was calculated.

6.4.4 Reliability of Supply

With the base yields calculated for each stochastic sequence, it was possible to calculate the long-term risk of failure and long-term reliability of supply as well as the recurrence interval of failures.

The base yields were sorted and ranked, and an extract of the base yields, along with their ranking position, is available in Appendix H.2. The ranked base yields were used to set up a yield-reliability curve and is presented in Figure 6.2.

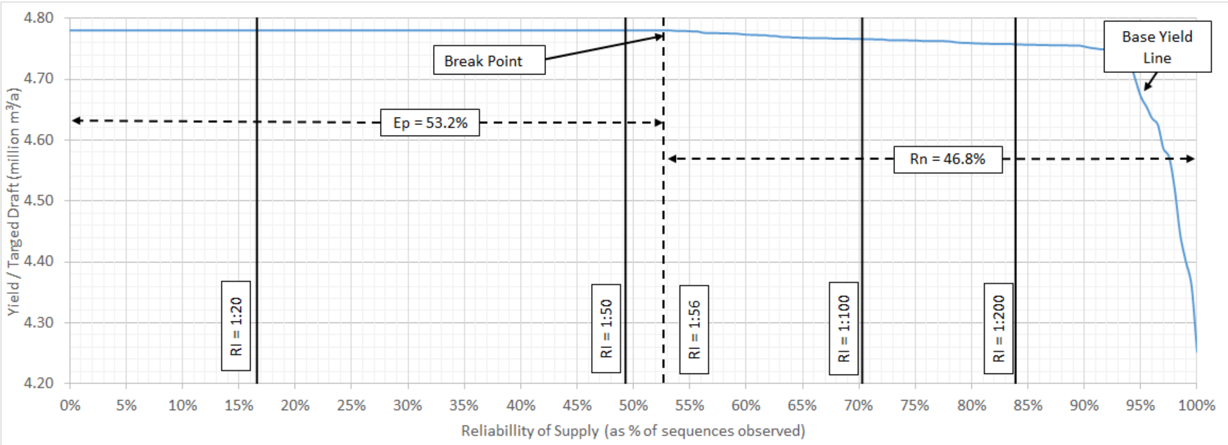

Figure 6.2: Yield-reliability curve for MIKE Hydro Basin without gains and losses

It was calculated that 94 of the 201 stochastic sequences had base yields smaller than the specified annual target draft of 4.78 million m^3. Therefore a total of 94 stochastic sequences failed to provide the specified annual target draft. The long-term risk of failure and longe-term reliability of supply, as well as the recurrence interval of failures, were calculated and the results are available in Table 6.4 and also graphically presented in Figure 6.2.

Table 6.4: Results of the calculated risk of failure, reliability of supply and recurrence interval of failures from MIKE Hydro Basin.

	Results
Risk of Failure	46.80%
Reliability of Supply	53.20%
Recurrence Interval	56 years

6.5 Summary

In this chapter two hydrological networks were analysed with MIKE Hydro Basin. Historical and stochastic yield analyses were done for both networks. The historical yield analyses revealed that Network 1 had a historical firm yield of 5.09 million m^3 while Network 2 had a historical firm yield of 4.79 million m^3. The stochastic yield analyses were done using the generated stochastic streamflow data from the WRYM in Chapter 5. For each network the 201 stochastic streamflows were imported into the model as historical streamflows and simulated. An long-term reliability of supply analysis was done for both networks and the results are summarised in Table 6.5.

Table 6.5: Summary of results of MIKE Hydro Basin

	Network 1	Network 2
Risk of Failure	38.80%	46.80%
Reliability of Supply	61.20%	53.20%
Recurrence Interval	72 years	56 years

The results from these analyses were compare to the results from the WRYM in Chapter 7.

Chapter 7

Comparison of the WRYM and MIKE Hydro Basin

In this chapter the results obtained from the historical and stochastic yield analyses by the WRYM and MIKE Hydro Basin in Chapters 5 and 6 were compared.

7.1 Network 1

In the first comparison Network 1 (Section 3.3.1) was set up in both simulation models. The network was analysed as described in Sections 5.1 and 6.2.

7.2 Historical Yield Analysis

In the historical yield analysis of Network 1 the historical firm yield was calculated by the WRYM to be 5.07 million m^3. The historical firm yield was also calculated manually for MIKE Hydro Basin to be 5.09 million m^3. The difference between the two historical firm yields is very small and can be ignored. This indicates that the WRYM is able to calculate a sufficient historical firm yield.

7.3 Stochastic Yield Analysis

The results of the stochastic yield analysis from the WRYM, the manually calculated results for the WRYM as well as the results calculated for MIKE Hydro Basin are summarised in Table 7.1.

Table 7.1: Comparison of results of Network 1 for the WRYM, manual calculations for WRYM and calculations for MIKE Hydro Basin

	WRYM	Manual Calculations	MIKE Hydro Basin
Number of Failed Sequences	19	75	78
Risk of Failure	9.95%	37.30%	38.80%
Reliability of Supply	90.05%	62.70%	61.20%
Recurrence Interval	334 years	75 years	72 years

From Table 7.1 it is clear that there is a big difference between the number of failed sequences calculated by the WRYM and those manually calculated for the WRYM and MIKe Hydro Basin. It was proved in Section 5.1.3 that the WRYM makes a possible mistake in the calculation of the number of failed sequences. The WRYM calculated that there were 19 stochastic sequences that failed to supply the specified annual target draft, but manual calculations revealed and that there were in fact 75 sequences that failed. It remains, however, unclear exactly how the WRYM calculates the number of failed stochastic sequences. The WRYM is very conservative in the calculation of stochastic sequence failures and therefore the long-term reliability of supply calculated by the model is also very conservative.

From the manually calculated results for the WRYM and MIKE Hydro Basin in Table 7.1 it is clear that there is not a big difference between the two models. In the analysis of the network with MIKE Hydro Basin only three more stochastic sequences, out of the 201, failed to supply the specified annual target draft than in the analysis with the WRYM. The main reason for this being that MIKE Hydro Basin does not take leap years into account. The WRYM also rounds values to four decimal places, while MIKE Hydro Basin does not round values and this also has a minor impact on the results.

7.4 Network 2

For the second comparison Network 2 (Section 3.3.2) was set up in both simulation models. The network was analysed as described in Sections 5.2 and 6.4.

7.5 Historical Yield Analysis

In the historical yield analysis of Network 2 the historical firm yield was calculated by the WRYM to be 4.78 million m^3. The historical firm yield was also calculated manually for MIKE

Hydro Basin to be 4.79 million m^3.

7.5.1 Evaporation and Precipitation

In the analysis of Network 2, evaporation and precipitation on the reservoir surface were considered. The evaporation and precipitation for both models were calculated and distributed as described in Sections 5.2 and 6.4.

When the evaporation and precipitation results from Appendix J and Appendix K are considered, it is clear that there is not a big difference between the evaporation and precipitation volumes on the reservoir surface calculated by the two models. The only difference is noticed at the evaporation and precipitation calculated for February. This small difference exists because the WRYM considers leap years in its calculation process, while MIKE Hydro Basin does not consider leap years. The difference between the two models is, however, small and can be ignored.

7.5.2 Reliability of Supply

The results of the stochastic yield analysis of Network 2, from the WRYM, the manually calculated results for the WRYM as well as the results calculated for MIKE Hydro Basin are summarised in Table 7.2.

Table 7.2: Comparison of results of Network 2 for the WRYM, manual calculations for WRYM and calculations for MIKE Hydro Basin

	WRYM	Manual Calculations	MIKE Hydro Basin
Number of Failed Sequences	30	95	94
Risk of Failure	15.42%	47.30%	46.80%
Reliability of Supply	84.58%	52.70%	53.20%
Recurrence Interval	209 years	55 years	56 years

From Table 7.2 it is again clear that there is a big difference between the number of failed sequences calculated by the WRYM and those manually calculated for the WRYM and MIKe Hydro Basin. This is the result of the same problem in Section 7.1.

From the manually calculated results for the WRYM and MIKE Hydro Basin in Table 7.2 it is clear that there is not a big difference between the two models. In the analysis of the network with MIKE Hydro Basin only one less stochastic sequence, out of the 201, failed to supply the specified annul target draft than in the analysis with the WRYM. This again is the result of

MIKE Hydro Basin not taking leap years into account and not rounding values, as opposed to the WRYM taking leap years into account and rounding its values to four decimal places.

7.6 Practicality of the WRYM and MIKE Hydro Basin

After both models were used to set up and analyse hydrological simulations, it was possible to compare the models in terms of their practicality and ease of use. The comparison of the practicality of the two models is presented in Table 7.3.

Table 7.3: Practicality comparison of the WRYM and MIKE Hydro Basin

	WRYM	MIKE
Data format	Data has to be in a specific format.	Data can be in any format.
	Can only handel certain units.	Able to handel all types of units.
Model setup	Extremely complicated, require assistance or training to set up model.	Very user friendly. Easy to set up model with only the assistance of the user manual.
GUI	Makes use of old Windows Viso 2003 software to set up model.	Has a built in modeling framework that is very userfriendly and easy to use.
	Only able to use the old software and is therefore prone to have problems on newer opperating systems.	
Results	Presents all numerical results in a single file.	User can specify which results is required and only save those results.
	Cannot choose which results has to be saved.	
Graphical representation of results	Has a good graphical representation of all the results.	Has a good graphical representation of all the results.
Stochastic streamflow generation	Is able to generate stochastic streamflows	Is not able to generate stochastic streamflows
Historical yield analysis	Is able to do a historical yield analysis of a hydrological system.	Is not able to do historical yield analyses.
Assurance of supply analysis	Is able to do an assurance of supply analysis for a hydrological system	Is not able to do an assurance of supply analyses.
User manual	Extremely complicated and technical.	Very user friendly and easy to use.
	Difficult to use without any assistance or training.	

From Table 7.3 it is established that MIKE Hydro Basin is the more practical and user-friendly hydrological simulation model of the two models discussed in this research. The WRYM is a more technical model and is able to generate stochastic streamflows and do historical yield analyses as well as long-term reliability of supply analyses, as opposed to MIKE Hydro Basin which is only able to simulate a hydrological system.

7.7 Summary

From all the data collected, analysed and compared, it was possible to obtain a good perspective of which model is the best to use under the prescribed circumstances.

From the literature in Section 2.7 it was established that the WRYM is able to do automated historical and stochastic yield analyses internally. The WRYM is able to calculate the historical firm yield on its own through iterations and also generates its own stochastic streamflow sequences for a stochastic yield analysis. The WRYM uses generated stochastic streamflow sequences to do determine the long-term reliability of supply of a hydrological system. It was established in Chapter 5 that the WRYM makes a possible mistake in the calculation of the total number of failed stochastic sequences. It was, however, not possible to determine exactly how the WRYM calculates the number of failed stochastic sequences.

From the literature in Section 2.8 it was established that MIKE Hydro Basin is not able to do an automated historical yield analysis or generate and analyse stochastic streamflow sequences. MIKE Hydro Basin can only be used to simulate a single hydrological sequence. The stochastic sequences generated by the WRYM were therefore imported into MIKE Hydro Basin as historical streamflow sequences and analysed manually (Chapter 6).

Two hydrological networks were analysed using the WRYM and MIKE Hydro Basin. Network 1 was a basic network without any evaporation or precipitation from the reservoir, while Network 2 took evaporation and precipitation into consideration. Both models were analysed manually and from the results it was clear that there is not a big difference between the manner in which the two models handle the various hydrological data. The only real difference between the two models is that the WRYM accounts for leap years in its calculation process, while MIKE Hydro Basin does not consider leap years. The difference is, however, so small that it does not have a great impact on the results.

Both models are considered to be good models to simulate and analyse a hydrological network. The WRYM is a very technical model and is the best model to use for a historical yield analysis, as it is designed for this specific purpose and is able to generate its own stochastic sequences. The WRYM is also able to do a stochastic yield analysis; it should, however, be noted that the WRYM makes possible errors in its calculation procedures and the results should be checked before they are used. MIKE Hydro Basin is a more practical and user-friendly model than the WRYM, but is not able to generate stochastic streamflow sequences or do an automated historical yield analysis or long-term reliability of supply analysis.

Chapter 8

Conclusion

In this research a full in-depth analysis of two stochastic streamflow generators, STOMSA and SAMS, was done. The purpose of the analysis was to compare STOMSA, which is the most common stochastic streamflow generator used in South Africa by the Department of Water and Sanitation, with SAMS, which is a stochastic streamflow generator developed and used in the United States of America.

From the analysis in Chapter 4 it was established that both STOMSA and SAMS are good stochastic streamflow generators. The stochastic streamflow data generated using STOMSA, with the default selected marginal distribution and time-series distribution of the generator, proved to be much more realistic than the stochastic data generated by SAMS. While SAMS also generated satisfying stochastic streamflow sequences, the variance in the average annual streamflows was exceptionally high. The results in Section 4.4 proved that STOMSA is indeed one of the better stochastic streamflow generators to use for South African streamflow conditions.

Components of STOMSA is also built into the WRYM, which is the hydrological simulation model used by the Department of Water and Sanitation in South Africa. However, STOMSA is still required to generate the parameters for the WRYM stochastic model. The WRYM and MIKE Hydro Basin, which is another hydrological simulation model created by the Danish Hydraulic Institute (DHI), were also analysed and compared with each other. The analysis was based on how each model handles stochastic streamflows and how they go about their modelling process.

The WRYM was discussed in Chapetr 5 and was used to generate stochastic streamflow sequences and do a historical and stochastic yield analysis. From the stochastic yield analysis it was discovered that the WRYM makes a possible mistake when it determines the number of stochastic streamflow sequences that fail to supply the specified annual target draft in the model. The amount of sequences that it determines to be failures is far less than the actual amount of sequences that fail to supply the specified annual target draft. The result is that the hydrological system proves to be much more reliable than in reality.

Additional analyses were done for WRYM to determine if the calculation problem of the WRYM is only restricted to the latest version of the WRYM (WRMF 4.3.0.0), and if the data that was used in the analysis was valid. From the analyses is was clear that the older version of the WRYM (WRIMS 3.8.2) makes the same calculation error as the latest version of the WRYM. An additional set of data was used for further analyses and also resulted in contradicting answers between the WRYM and the manual calculations. It was established that in the case where the specified annual target draft is much higher than the historical firm yield, the WRYM presents the correct number of failed stochastic sequences that matches the number of failed stochastic sequences calculated manually. However, when the specified annual target draft is close to the historical firm yield, the WRYM is very conservative in the calculation of the number of failed stochastic sequences. The WRYM also validates the data and network used for a simulation and no errors were reported by the model in all the simulations.

It was, however, not possible to determine exactly how the WRYM calculates the number of failed sequences, since the program source code was not available.

In the WRMF Version 4.3.0.0 it is indicated as if the model uses a constant number of 28.5 days for February whenever the model converts data to cubic meters per second, in order to take leap years into account. It was, however, proved that the WRYM does not use a constant of 28.5 days for February, but rather calculates an average value over 4 years when it converts data into cubic meters per second.

After these problems were discovered within the WRYM a manual analysis of the generated stochastic streamflow sequences was done in order to obtain results that were comparable with that of MIKE Hydro Basin.

From the literature in Section 2.8.3 it is seen that MIKE Hydro Basin is simply used to simulate hydrological systems and is not able to generate and analyse its own stochastic streamflow sequences. The same stochastic streamflow sequences that were generated in the WRYM were imported into MIKE Hydro Basin and analysed individually as historical streamflow files in Chapter 6.

From the analysis it was discovered that MIKE Hydro Basin does not take leap years into account whenever it converts data to cubic meters per second. It was, therefore, necessary to convert all data manually and import the converted data directly into the model in order to obtain results that could be compared to that of the WRYM.

All the results from the WRYM and MIKE Hydro Basin were compared and are available in Tables 7.1 and 7.2 in Chapter 7. From the results it is seen that there is not a big difference between the two models. Both models are good hydrological simulation models.

In the case where a yield analysis is required, historical or stochastic, the WRYM is the best model to use as it was designed for that purpose. The WRYM has been used for many projects all over South Africa and it would be wrong to discredit the model. The results obtained from the WRYM in this thesis, however, proved not to be trustworthy and therefore all results from the WRYM should be checked before they are presented or used elsewhere.

MIKE Hydro Basin on the other hand is more user friendly and easier to use in the case of a simple hydrological streamflow simulation.

Chapter 9

Recommendations

The purpose of this research was to identify and compare stochastic streamflow generators, and to use these generators within the WRYM and MIKE Hydro Basin.

STOMSA and SAMS were found to be two stochastic streamflow generators capable of generating satisfying stochastic streamflow data. The only problem is the high variance in the average annual streamflows between the sequences generated by SAMS. Further studies should focus on why there is such a big variance, whether it is a mathematical problem, or whether it has something to do with the fact that SAMS is an American product and the data used for the analyses came from South Africa.

The WRYM and MIKE Hydro Basin were used to perform yield analyses. While the WRYM is capable of generating and analysing stochastic streamflow sequences, it was discovered that it makes a possible calculation mistake in the analysis process. The WRYM makes a possible mistake in the calculation of the number of failed stochastic streamflow sequences. Further studies should look into the problem and aim to rectify it.

MIKE Hydro Basin is a hydrological simulation model. The model can only be used to simulate single hydrological data sets and is not capable of stochastic streamflow generation or analysis. It is recommended that further development of the model should include a stochastic streamflow generator and yield analysis process in the model. In order to improve the accuracy of MIKE Hydro Basin, it is recommended that the model should take leap years into account in its simulation process.

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Appendices

Appendix A

Historical Streamflow Data of Flow Station C9R002 at Bloemhof Dam

Table A.1: Historical test streamflow data from flow station C9R002 (million m^3/s)

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Total
1920	6.29	2.64	1.33	3.46	9.91	234.34	80.28	1.87	1.46	1.24	1.07	0.95	344.84
1921	0.87	24.68	102.70	41.73	4.05	1.20	0.96	0.79	0.82	0.84	0.99	0.89	180.52
1922	1.11	23.26	11.66	21.72	55.11	17.86	1.35	1.20	1.15	1.15	1.06	0.87	137.50
1923	0.73	1.02	0.69	5.96	3.17	34.24	12.44	1.07	0.93	0.88	0.84	1.20	63.17
1924	4.28	25.97	19.67	15.93	9.97	269.12	97.29	5.36	2.62	1.78	1.33	1.12	454.44
1925	0.98	1.53	1.00	3.43	10.66	7.95	2.30	0.87	0.86	0.87	0.82	0.75	32.02
1926	1.33	1.14	4.46	5.78	4.16	23.80	8.66	1.00	0.88	1.11	1.11	0.87	54.30
1927	1.95	1.09	1.38	43.09	20.10	8.56	3.28	1.20	1.05	0.96	0.91	0.98	84.55
1928	1.46	7.10	3.26	24.40	9.58	9.55	4.16	1.33	1.57	1.56	1.26	11.69	76.92
1929	5.03	19.80	26.66	34.08	12.65	6.45	3.23	1.47	1.17	1.06	0.97	0.84	113.41
1930	0.69	0.67	3.68	32.84	13.92	5.27	41.46	14.40	1.11	1.00	0.91	0.75	116.70
1931	1.46	20.73	7.48	0.69	17.03	8.84	1.87	0.97	0.87	0.82	0.78	0.70	62.24
1932	0.62	0.93	12.36	4.55	0.76	1.18	1.00	0.82	0.74	0.71	0.69	0.62	24.98
1933	0.55	75.73	51.98	367.63	123.81	5.63	2.74	12.90	5.46	1.53	1.38	1.06	650.40
1934	4.25	106.46	44.87	3.88	1.51	28.39	10.73	1.32	1.03	0.93	0.84	0.74	204.95
1935	0.66	2.77	6.47	6.72	11.91	73.03	25.13	3.61	2.59	1.59	1.21	0.99	136.68
1936	0.97	199.21	68.31	39.20	21.16	5.40	1.77	1.05	0.91	0.84	0.78	0.69	340.29
1937	0.62	0.55	15.60	23.93	17.62	4.47	4.94	2.52	1.15	1.09	1.11	0.93	74.53
1938	10.70	4.07	15.71	32.36	50.86	26.54	5.61	1.47	1.29	1.79	1.74	1.30	153.44
1939	1.74	11.63	5.30	3.26	2.08	5.58	3.20	1.44	1.24	1.14	1.00	1.15	38.76
1940	0.95	4.66	15.63	28.95	22.36	5.69	2.26	1.52	0.98	0.87	0.79	0.73	85.39
1941	1.66	0.93	1.33	38.69	17.77	11.61	4.65	1.31	1.06	0.96	0.97	0.88	81.82

1942	5.95	5.30	77.66	32.02	3.35	5.34	48.25	57.70	15.45	2.58	2.23	1.54	257.37
1943	21.03	68.89	72.23	24.13	230.19	82.24	2.26	1.33	4.72	3.21	1.63	2.26	514.12
1944	6.54	11.83	4.13	2.29	2.62	75.78	27.11	1.44	1.17	1.06	0.93	0.79	135.69
1945	0.66	0.57	0.69	22.51	14.75	46.75	16.42	1.64	1.33	1.15	1.00	0.84	108.31
1946	4.32	2.49	1.60	8.26	8.33	11.68	8.16	2.77	1.24	1.05	0.91	0.80	51.61
1947	0.73	1.03	21.49	16.99	4.06	190.77	67.00	2.44	1.42	1.15	1.00	0.84	308.92
1948	0.97	4.95	2.06	12.03	4.63	1.71	1.15	0.79	0.80	0.84	0.80	0.73	31.46
1949	1.57	9.10	40.79	17.85	7.18	36.16	34.41	46.86	15.09	2.07	1.56	1.18	213.82
1950	0.96	0.79	43.03	21.81	4.09	3.73	4.12	2.46	1.65	1.44	1.28	1.02	86.38
1951	7.95	3.26	1.26	2.64	8.57	3.41	0.96	0.88	0.82	1.11	1.09	0.83	32.78
1952	0.87	15.42	29.61	9.00	51.14	20.85	3.06	1.66	1.23	1.07	0.96	0.82	135.69
1953	3.12	5.09	3.88	6.30	15.17	17.50	5.36	1.20	1.11	1.05	0.93	0.82	61.53
1954	0.73	3.08	7.02	70.75	92.03	25.49	6.36	3.28	1.62	1.33	1.11	0.91	213.71
1955	1.80	2.75	8.52	3.17	45.98	38.08	8.46	1.69	1.44	1.12	0.95	0.84	114.80
1956	6.93	3.52	61.71	57.52	15.40	5.39	2.54	1.18	1.66	2.22	2.08	103.24	263.39
1957	54.13	9.09	15.03	94.58	31.22	1.68	2.90	2.68	2.02	1.55	1.29	1.28	217.45
1958	1.12	2.93	11.67	7.65	2.59	1.20	4.83	3.35	2.04	1.51	1.06	0.73	40.68
1959	3.15	1.74	20.65	5.01	7.86	11.94	5.36	3.50	1.90	1.51	1.37	1.23	65.22
1960	1.23	1.79	72.86	29.04	2.50	2.21	30.80	14.65	0.70	3.98	1.97	0.80	162.53
1961	0.32	37.55	12.93	0.00	17.76	14.73	12.12	5.09	1.71	0.91	0.37	0.00	103.49
1962	0.00	12.60	7.42	37.91	14.13	0.18	0.00	1.48	2.78	1.98	1.06	0.00	79.54
1963	0.23	19.70	10.74	2.24	1.06	17.70	3.91	1.33	1.56	0.31	0.00	0.00	58.78
1964	52.09	9.77	6.58	14.56	4.61	0.00	2.46	1.79	1.17	1.14	0.42	0.00	94.59
1965	0.00	0.00	0.00	7.20	58.98	25.61	1.15	0.73	0.98	0.58	0.00	0.00	95.23
1966	1.02	1.52	13.59	158.05	120.07	42.58	56.79	20.62	2.59	1.71	1.32	1.09	420.95
1967	0.93	1.54	1.50	0.78	0.56	14.25	7.02	1.93	1.21	0.96	0.84	0.73	32.25
1968	0.40	1.23	4.63	1.72	0.57	2.66	1.54	18.90	6.98	0.78	0.60	0.48	40.49
1969	7.87	3.97	4.23	7.21	2.77	0.84	0.79	0.82	0.84	0.97	0.94	0.84	32.09
1970	0.61	2.35	15.07	16.51	5.12	1.42	5.34	2.72	1.02	0.78	0.66	0.57	52.17
1971	0.00	0.00	11.58	47.00	13.14	19.92	5.16	0.00	0.00	0.67	1.46	0.84	99.77
1972	0.38	0.78	0.60	1.35	14.61	5.29	2.00	1.20	0.63	0.54	0.55	0.99	28.92
1973	2.44	7.01	21.73	51.34	81.03	11.12	38.63	4.10	2.80	2.23	1.17	4.34	227.94
1974	0.45	31.07	19.34	2.37	160.13	80.16	29.56	8.86	5.59	6.58	5.94	5.57	355.62
1975	0.00	0.00	50.41	150.07	165.82	178.83	32.64	53.93	7.98	7.83	7.65	3.28	658.44
1976	60.02	29.45	0.78	0.00	101.98	22.73	6.58	2.24	6.92	6.17	4.16	7.33	248.36
1977	12.63	7.09	10.39	2.02	78.41	60.14	65.66	14.19	10.50	11.24	8.68	8.24	289.19
1978	18.11	5.15	6.69	8.10	10.19	2.50	2.83	4.21	5.17	6.07	30.65	13.89	113.56
1979	0.00	0.09	4.79	0.00	3.54	19.81	4.36	3.13	3.31	3.61	3.37	6.32	52.33
1980	3.97	11.61	41.77	33.61	24.26	71.27	7.71	3.12	4.31	4.91	3.76	4.89	215.19
1981	3.65	6.47	26.93	19.08	4.10	3.47	31.93	11.26	3.65	3.34	3.80	2.78	120.46

1982	16.92	9.28	1.99	2.44	1.84	0.00	1.33	1.02	4.41	2.77	1.31	0.00	43.31
1983	9.42	22.28	9.05	2.06	0.78	3.83	1.75	0.61	0.61	0.65	0.84	0.71	52.59
1984	5.89	5.68	2.13	14.71	12.05	6.21	2.11	0.97	0.91	0.87	0.82	0.73	53.08
1985	5.67	2.35	9.61	6.05	1.57	2.44	3.22	1.59	0.95	0.91	1.00	0.96	36.32
1986	3.78	22.18	9.17	13.05	0.36	0.00	0.00	0.00	0.00	0.00	2.08	62.88	113.50
1987	32.93	10.01	11.70	8.31	0.00	295.93	17.69	7.20	1.88	3.73	3.70	3.89	396.97
1988	42.06	39.82	9.31	77.80	110.32	35.43	10.88	13.07	5.57	5.12	7.35	2.02	358.75
1989	3.25	11.66	13.17	9.13	9.86	18.22	26.79	9.84	4.15	2.21	5.06	8.02	121.36
1990	0.76	0.00	3.53	42.63	37.72	17.17	3.10	0.00	1.65	3.74	3.77	2.81	116.88
1991	10.94	4.58	2.66	2.62	0.00	0.00	0.15	0.00	0.00	0.00	0.00	4.50	25.45
1992	0.00	86.33	7.47	5.21	12.41	2.05	0.60	0.00	0.48	0.00	0.00	0.00	114.55
1993	3.98	0.00	0.00	32.81	38.73	13.25	2.50	2.47	2.54	3.70	4.57	1.84	106.39
1994	0.60	0.91	0.99	9.55	3.73	15.25	5.87	1.02	0.93	0.84	0.78	0.71	41.18

Appendix B

STOMSA and SAMS Crushed Generated Data

Table B.1: STOMSA crushed generated data (million m^3/s)

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Total
1920	6.75	14.24	17.41	22.80	20.31	27.42	11.43	3.77	2.04	1.69	1.66	2.78	132.31
1921	7.68	16.99	22.44	23.28	36.63	27.11	11.67	3.97	2.29	1.68	1.45	3.75	158.96
1922	6.88	22.56	25.13	23.84	27.98	33.59	15.53	5.69	2.50	1.98	1.81	2.72	170.21
1923	7.90	10.29	20.88	27.62	28.95	27.35	13.36	5.13	2.53	2.23	1.91	3.73	151.90
1924	6.27	16.28	27.10	19.01	24.99	28.28	11.21	4.27	1.97	1.82	1.55	3.53	146.29
1925	6.60	13.97	18.71	25.42	30.85	37.73	14.81	3.93	2.09	2.06	1.79	2.68	160.64
1926	7.00	17.08	21.24	38.38	30.01	21.77	11.04	4.65	2.43	1.94	1.60	3.68	160.82
1927	5.48	14.67	23.86	27.11	24.35	34.85	13.50	4.96	2.07	1.86	2.04	1.63	156.37
1928	8.06	12.80	20.25	21.35	21.06	31.54	14.59	5.97	2.77	2.03	2.08	4.87	147.38
1929	8.05	14.46	18.42	25.13	28.26	31.43	13.11	3.25	2.16	1.89	1.68	2.62	150.45
1930	8.24	21.71	20.56	21.82	39.25	26.16	9.43	3.63	2.09	1.78	1.45	1.56	157.67
1931	8.29	16.70	21.25	18.77	26.42	37.84	18.69	4.88	2.86	2.67	2.56	2.43	163.37
1932	7.85	15.23	21.56	35.43	32.94	27.58	12.51	4.47	2.23	1.63	1.56	3.83	166.81
1933	8.92	19.77	25.77	25.85	34.67	29.26	11.31	3.80	2.14	1.77	1.53	2.42	167.21
1934	9.69	17.97	22.90	32.80	40.01	28.76	10.12	3.71	2.38	1.93	2.11	6.91	179.27
1935	9.37	12.73	18.56	26.37	30.66	34.98	17.81	6.44	2.83	2.11	1.80	2.89	166.55
1936	6.34	20.48	24.60	27.92	27.61	22.61	11.55	4.36	1.93	1.75	1.51	3.63	154.29
1937	7.10	16.12	21.26	24.84	28.85	26.29	11.33	4.98	1.98	1.76	1.50	3.46	149.47
1938	5.81	11.73	18.51	21.16	19.86	26.57	12.30	3.65	1.94	1.46	1.28	6.60	130.89
1939	6.93	15.63	20.58	20.61	29.19	32.04	11.08	4.37	2.28	1.87	1.53	2.01	148.11
1940	8.26	12.77	18.08	21.16	24.62	36.71	13.52	4.69	2.20	1.96	1.66	4.51	150.13
1941	9.27	15.16	18.77	16.63	22.70	38.85	13.90	4.02	2.42	2.14	1.92	3.92	149.71

1942	5.37	13.04	20.25	26.87	32.10	40.89	17.23	5.25	2.44	2.18	1.83	3.72	171.17
1943	8.40	17.33	22.53	24.73	33.79	30.89	12.63	3.28	2.12	1.79	1.54	3.56	162.58
1944	5.63	10.42	17.81	17.66	19.87	23.54	12.51	3.77	2.01	1.70	1.46	3.66	120.02
1945	6.18	14.27	16.21	29.04	30.25	31.34	11.88	4.74	2.29	1.81	1.59	2.62	152.22
1946	10.73	15.69	18.57	18.28	26.47	37.10	11.07	3.21	2.29	2.17	2.11	4.53	152.22
1947	6.15	13.85	20.40	31.15	29.93	24.78	12.82	4.41	2.30	1.85	1.79	3.80	153.23
1948	6.34	12.93	20.44	23.78	31.17	27.99	14.17	6.35	2.59	1.96	1.70	2.12	151.54
1949	5.52	20.23	21.81	23.97	27.96	29.61	10.22	4.31	1.93	1.78	1.66	2.63	151.63
1950	7.25	14.97	18.43	26.64	27.09	25.77	10.72	3.64	2.10	1.78	1.46	2.35	142.21
1951	6.25	21.61	24.23	28.27	26.72	29.95	11.79	3.83	1.97	1.51	1.29	5.63	163.04
1952	7.18	19.55	23.40	24.82	34.62	37.52	14.26	4.61	2.56	2.11	1.97	3.36	175.94
1953	6.59	15.27	21.07	25.47	24.44	33.66	11.98	3.47	2.04	1.93	1.71	3.01	150.64
1954	6.66	14.25	22.29	29.31	23.87	32.44	11.90	5.27	2.23	1.81	1.63	5.29	156.94
1955	7.16	19.24	24.40	28.27	27.19	23.23	12.24	5.64	2.83	1.92	1.71	5.77	159.61
1956	9.51	13.99	17.29	23.67	30.20	40.12	13.87	3.88	2.23	1.98	1.65	4.83	163.21
1957	10.21	16.03	20.02	30.08	33.41	33.77	13.24	4.20	2.48	2.09	1.74	3.02	170.28
1958	8.22	15.47	24.40	29.52	23.25	31.97	12.87	3.22	1.81	1.70	1.47	4.64	158.54
1959	5.76	12.38	18.04	24.74	27.63	25.07	12.44	3.34	1.97	1.55	1.64	4.52	139.08
1960	5.74	16.29	20.65	25.65	32.42	30.66	13.28	5.27	2.48	2.07	1.79	4.99	161.29
1961	9.31	14.43	16.01	16.92	22.75	34.88	11.37	3.67	2.26	1.95	2.01	2.77	138.32
1962	6.66	10.77	21.17	26.37	24.99	24.74	8.89	5.74	2.28	1.99	1.83	2.60	138.02
1963	7.18	19.01	21.09	21.15	28.61	27.06	13.22	4.08	2.14	1.99	1.90	3.31	150.75
1964	8.28	10.94	19.70	24.61	29.54	31.92	13.03	4.57	2.18	2.04	1.93	4.86	153.60
1965	6.18	13.81	16.09	26.67	28.35	39.90	13.48	4.41	2.17	1.91	1.64	1.63	156.23
1966	6.40	24.14	23.77	28.16	26.72	22.89	9.88	3.25	1.79	1.55	1.31	1.53	151.39
1967	8.37	12.53	18.58	15.65	20.48	22.77	9.84	3.17	2.08	1.78	1.50	4.60	121.34
1968	5.88	16.15	18.79	41.52	27.83	35.86	15.09	4.12	2.12	1.72	1.61	3.26	173.94
1969	6.94	20.04	24.14	26.63	30.14	44.81	15.30	4.23	2.31	1.89	1.64	4.88	182.95
1970	7.14	15.52	20.37	21.00	25.86	26.91	10.59	3.54	1.96	1.84	1.77	3.89	140.41
1971	7.41	12.53	21.53	31.19	32.04	34.86	13.50	5.31	2.41	1.97	1.62	3.15	167.51
1972	7.66	13.58	22.38	25.83	34.91	35.34	14.27	4.20	2.41	2.06	1.71	4.07	168.41
1973	6.69	17.04	21.47	21.19	33.03	26.42	9.57	3.15	2.29	2.03	2.17	4.04	149.07
1974	7.95	16.01	18.31	28.35	27.34	26.06	11.84	3.97	2.28	1.85	1.68	2.24	147.88
1975	9.17	13.75	20.46	20.60	38.04	27.56	12.38	3.55	2.34	2.13	1.82	2.91	154.71
1976	7.31	20.22	20.14	18.58	31.35	29.96	12.75	4.01	2.28	2.11	1.81	1.77	152.30
1977	6.58	18.09	22.85	27.40	33.59	41.48	13.95	4.59	2.24	1.95	1.78	4.66	179.15
1978	8.35	17.48	22.31	17.80	19.07	44.92	15.52	4.02	2.11	1.61	1.29	4.62	159.10
1979	7.59	9.85	20.73	18.17	25.63	35.96	13.13	4.57	2.38	1.94	1.95	3.10	144.99
1980	10.58	11.55	16.61	24.83	29.93	31.08	13.01	3.51	2.30	1.92	1.54	2.62	149.48
1981	9.00	15.30	18.06	21.36	24.86	23.05	10.93	3.48	2.15	1.84	1.49	2.85	134.36

1982	7.09	17.03	20.96	25.16	30.43	46.22	13.11	4.25	2.01	1.91	1.56	3.39	173.12
1983	8.90	13.08	20.98	22.59	22.40	37.16	17.03	5.03	2.25	1.96	1.64	3.61	156.64
1984	7.16	11.34	18.67	22.62	24.03	24.22	12.49	5.36	2.51	1.87	1.64	3.85	135.77
1985	5.77	21.52	23.62	30.41	28.48	39.84	17.17	4.28	2.12	1.75	1.64	5.03	181.65
1986	8.88	23.59	23.16	22.99	27.10	38.61	15.49	3.62	2.19	2.05	2.10	4.05	173.82
1987	6.60	16.05	22.66	22.38	27.38	38.20	15.70	4.59	2.16	2.05	1.75	1.82	161.36
1988	6.93	13.03	19.99	24.75	31.46	29.27	14.96	4.03	2.14	1.90	1.81	3.67	153.94
1989	10.00	12.61	18.91	22.95	25.92	23.91	12.00	5.08	2.44	1.99	1.70	3.67	141.19
1990	7.73	17.97	21.21	25.88	24.83	36.22	12.70	4.21	2.14	1.92	1.97	3.51	160.29
1991	6.67	18.05	19.19	28.91	27.38	22.15	10.68	4.49	2.54	2.18	1.84	3.85	147.93
1992	9.63	10.12	17.86	28.25	27.45	32.52	11.84	5.71	2.68	2.01	1.72	4.93	154.73
1993	9.23	12.07	19.22	19.19	28.74	33.67	12.60	3.91	1.99	1.99	1.68	1.64	145.94
1994	7.35	17.34	25.97	24.04	25.71	24.67	11.09	3.60	2.09	1.76	1.51	3.44	148.59

Table B.2: SAMS crushed generated data

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Total
1920	5.92	18.47	18.42	38.66	31.94	43.46	17.46	7.30	2.95	2.27	2.76	6.94	196.56
1921	10.47	26.90	21.20	35.94	39.17	39.01	16.35	7.42	2.72	2.38	3.18	9.26	214.00
1922	9.60	19.49	20.59	38.20	37.05	47.51	17.56	7.69	2.90	2.17	2.67	8.56	214.00
1923	7.38	18.94	15.46	28.50	28.47	36.77	14.56	7.25	2.50	1.87	2.45	8.96	173.11
1924	6.20	18.77	20.02	42.07	34.45	42.94	17.33	6.51	2.68	2.31	2.76	8.14	204.17
1925	5.94	20.79	17.43	30.67	27.49	47.80	18.08	8.14	3.31	2.35	2.89	8.57	193.46
1926	6.55	22.22	18.56	35.15	35.56	39.99	14.75	7.96	2.64	2.16	2.86	8.93	197.32
1927	7.78	24.28	21.58	38.27	38.13	47.38	17.36	7.93	2.68	1.92	2.83	8.75	218.89
1928	5.25	25.77	21.85	36.25	37.19	37.96	14.70	6.29	2.56	1.83	2.49	6.53	198.66
1929	8.19	22.87	19.38	34.20	37.41	45.27	16.31	6.73	2.44	1.65	2.31	7.32	204.08
1930	4.55	17.13	19.96	33.74	34.40	44.92	15.69	8.57	2.72	1.95	2.39	8.94	194.95
1931	4.60	19.70	17.77	40.23	38.70	38.01	15.64	8.02	2.96	2.18	2.84	7.50	198.15
1932	7.24	18.21	20.13	35.04	32.54	37.12	14.83	7.19	2.60	2.05	3.19	7.70	187.84
1933	6.92	20.16	19.40	33.57	32.13	44.89	16.39	7.71	3.03	2.18	3.13	7.72	197.23
1934	12.06	17.03	18.38	35.20	33.33	50.63	18.62	7.13	2.72	2.14	2.80	7.76	207.78
1935	7.74	19.19	18.20	40.91	41.97	47.29	16.79	7.20	2.39	1.95	2.34	8.41	214.40
1936	9.17	18.54	19.13	33.20	34.32	40.09	16.05	6.45	2.68	2.22	3.12	8.67	193.63
1937	11.59	20.41	21.53	32.82	34.19	40.90	16.61	8.12	3.02	2.33	3.39	6.64	201.54
1938	9.52	16.38	17.24	34.01	33.28	43.83	18.52	9.36	3.42	2.05	2.45	7.33	197.40
1939	6.21	21.27	18.84	39.33	36.93	39.77	15.52	6.87	2.42	1.87	2.20	9.31	200.55
1940	9.62	16.76	20.03	36.39	35.12	46.77	18.33	8.97	3.05	2.08	2.63	8.04	207.81
1941	4.97	23.20	21.70	40.06	34.84	42.57	15.40	7.34	2.50	1.93	2.75	7.39	204.65

1942	7.10	17.20	18.39	40.91	34.33	37.64	13.90	6.51	2.33	1.99	2.53	7.51	190.34
1943	6.04	17.96	19.62	35.84	35.81	43.95	15.91	8.67	3.19	2.09	2.67	6.65	198.41
1944	8.23	22.62	20.43	36.10	36.22	48.48	17.20	7.75	2.65	1.77	2.39	5.61	209.45
1945	4.57	21.31	18.99	33.94	30.81	43.21	14.62	6.57	2.57	2.02	2.56	8.73	189.90
1946	8.62	21.94	22.01	38.84	37.11	47.95	16.75	8.36	2.87	2.03	2.88	6.98	216.35
1947	3.70	19.47	17.54	33.94	35.66	38.25	15.57	7.25	2.61	1.71	2.45	7.27	185.42
1948	6.74	23.49	21.13	36.48	40.58	49.58	16.79	6.63	2.75	2.38	2.86	8.17	217.59
1949	12.14	22.48	22.56	37.58	33.81	38.42	15.17	7.35	2.57	1.97	2.75	7.57	204.37
1950	5.77	16.99	19.35	38.11	33.48	48.69	15.49	6.07	2.52	2.00	2.74	7.18	198.40
1951	7.08	16.85	17.45	38.98	37.96	40.91	15.34	7.50	2.80	2.03	2.89	9.60	199.39
1952	4.52	18.53	16.05	35.29	33.46	45.70	16.88	7.22	2.57	1.94	2.63	8.79	193.56
1953	6.01	23.08	20.72	35.04	39.40	49.77	16.69	7.49	2.71	2.20	2.73	7.39	213.25
1954	5.84	23.30	19.69	33.48	28.99	39.06	14.96	7.68	2.90	2.22	2.77	6.78	187.67
1955	6.56	20.12	16.94	33.36	36.08	46.99	16.22	5.89	2.38	1.88	2.69	8.48	197.58
1956	5.76	21.65	20.68	36.51	30.23	33.82	14.65	7.51	3.23	2.33	3.39	9.99	189.75
1957	6.13	21.25	19.91	40.01	36.05	43.32	16.82	8.06	3.10	2.19	3.25	7.00	207.09
1958	7.32	14.03	20.23	35.11	28.61	33.43	15.65	8.05	3.02	2.18	2.86	6.79	177.28
1959	6.15	20.80	20.13	32.99	29.27	39.36	14.40	7.07	2.76	2.12	2.49	8.43	185.98
1960	5.92	17.45	18.05	31.79	29.69	44.30	15.31	8.10	2.90	2.23	2.72	8.10	186.56
1961	6.73	19.56	19.32	35.30	38.47	41.52	16.70	7.75	3.10	2.38	2.79	7.48	201.09
1962	5.87	18.01	18.99	36.38	34.02	43.82	13.94	7.13	2.69	2.21	2.99	7.27	193.30
1963	5.39	20.45	17.85	39.66	34.98	38.18	14.51	6.25	2.38	1.86	2.68	6.76	190.96
1964	4.73	20.30	19.57	33.65	35.03	43.59	17.90	7.26	2.76	2.23	2.93	8.74	198.68
1965	10.37	24.03	21.72	31.83	33.90	39.87	15.95	8.78	3.04	1.98	2.53	8.08	202.09
1966	11.42	14.48	16.57	29.88	27.24	44.37	15.97	7.15	2.41	2.03	2.09	6.43	180.06
1967	7.27	17.59	17.81	35.21	34.68	44.47	15.80	7.28	2.69	2.13	2.74	6.96	194.63
1968	4.39	17.33	18.81	44.49	36.30	39.34	17.14	8.36	2.81	2.00	2.36	8.60	201.93
1969	8.94	23.49	21.88	39.57	39.97	49.45	18.39	7.82	3.11	2.22	3.02	8.33	226.20
1970	7.15	19.29	16.32	41.90	37.46	41.65	15.77	7.97	2.79	2.14	2.61	6.96	202.01
1971	4.06	22.84	18.20	35.53	30.10	43.01	12.70	7.30	2.93	2.12	2.54	7.23	188.56
1972	7.00	19.37	21.60	43.10	38.74	44.66	18.32	8.69	2.98	1.92	2.60	6.89	215.88
1973	5.73	21.49	23.36	37.65	34.12	32.91	15.56	8.15	2.98	2.21	2.95	5.78	192.88
1974	6.16	18.45	20.28	35.00	29.51	39.89	16.47	8.41	2.93	2.06	2.84	7.04	189.03
1975	6.61	16.60	16.30	35.60	31.92	40.80	16.22	7.51	2.74	2.01	2.70	7.89	186.91
1976	8.48	22.32	19.62	33.97	35.13	33.23	12.03	6.35	2.21	1.61	2.13	10.06	187.13
1977	9.48	19.52	19.83	37.47	41.76	51.82	18.27	7.25	2.75	2.05	2.95	6.67	219.82
1978	4.52	19.70	20.48	37.23	36.33	42.95	17.30	7.67	2.96	2.33	3.09	7.50	202.07
1979	6.61	19.19	17.03	40.88	35.15	40.16	16.38	7.15	2.55	1.86	2.35	7.05	196.38
1980	8.30	18.30	20.29	34.54	34.37	38.72	16.40	7.91	3.02	2.14	3.05	6.81	193.88
1981	4.66	18.94	16.67	32.19	30.77	36.93	17.73	7.05	2.86	2.25	2.77	8.02	180.83

1982	9.29	20.01	22.54	40.08	38.90	47.98	17.50	7.42	2.66	2.07	2.73	10.11	221.28
1983	8.00	23.59	22.40	42.15	36.40	39.71	16.41	7.71	2.62	2.35	3.32	8.74	213.39
1984	10.65	19.39	17.73	34.16	29.98	36.61	16.03	8.05	3.19	2.18	2.93	6.90	187.80
1985	10.82	22.28	20.40	39.01	40.25	45.29	19.77	8.25	3.22	2.23	3.03	7.20	221.75
1986	8.05	16.83	20.27	34.44	33.81	39.88	17.93	7.98	3.13	2.22	2.80	9.25	196.60
1987	6.03	19.64	16.81	35.31	36.16	44.76	15.68	6.64	2.44	1.97	2.44	6.89	194.76
1988	6.98	19.75	17.93	33.90	39.58	38.97	14.81	8.13	2.95	2.09	2.43	6.40	193.92
1989	5.74	18.79	17.60	35.02	33.51	43.03	16.34	6.49	2.57	1.90	2.89	8.10	191.98
1990	6.51	17.31	18.14	35.45	41.68	40.12	16.92	9.36	3.15	2.01	2.46	7.89	200.98
1991	10.23	16.82	18.09	29.41	37.12	50.81	18.86	8.07	3.00	1.94	2.41	7.38	204.13
1992	12.95	19.02	17.99	37.92	36.17	41.18	14.67	7.21	2.63	2.12	2.67	9.03	203.55
1993	9.02	21.36	20.47	34.43	35.93	39.13	15.59	8.38	3.11	2.05	2.92	10.05	202.45
1994	4.35	23.36	20.51	36.91	40.38	47.41	15.85	6.87	2.53	2.10	2.60	6.47	209.34

Appendix C

Generated Stochastic Streamflow Data

C.1 SAMS

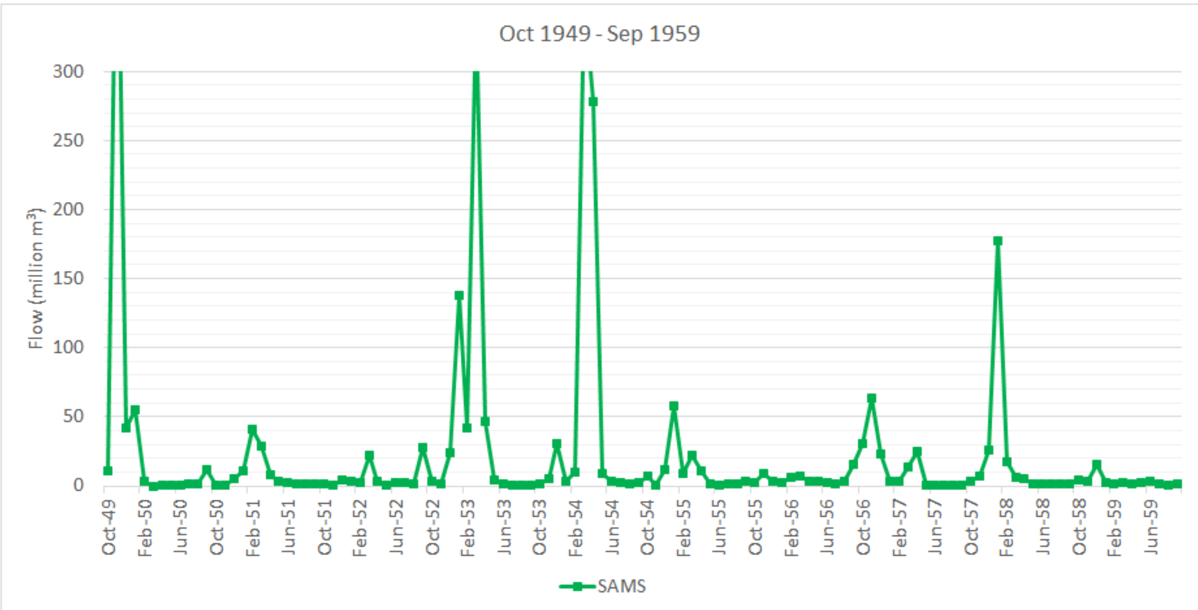

Figure C.1: SAMS generated streamflow data sequence 28 using a 3-parameter log-normal distribution

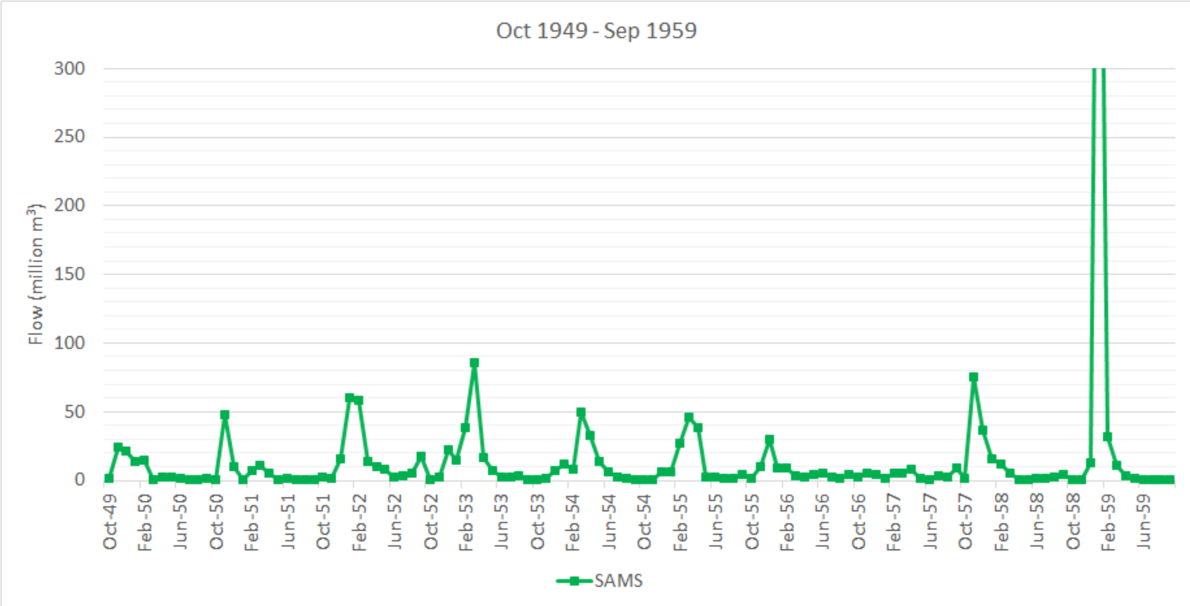

Figure C.2: SAMS generated streamflow data sequence 40 using a 3-parameter log-normal distribution

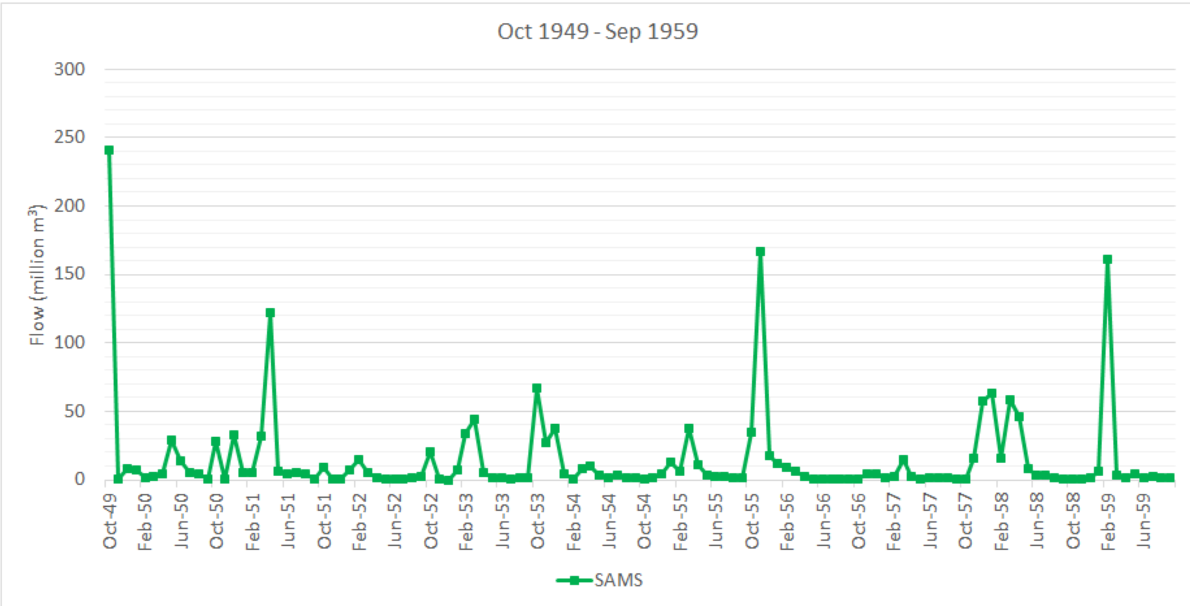

Figure C.3: SAMS generated streamflow data sequence 63 using a 3-parameter log-normal distribution

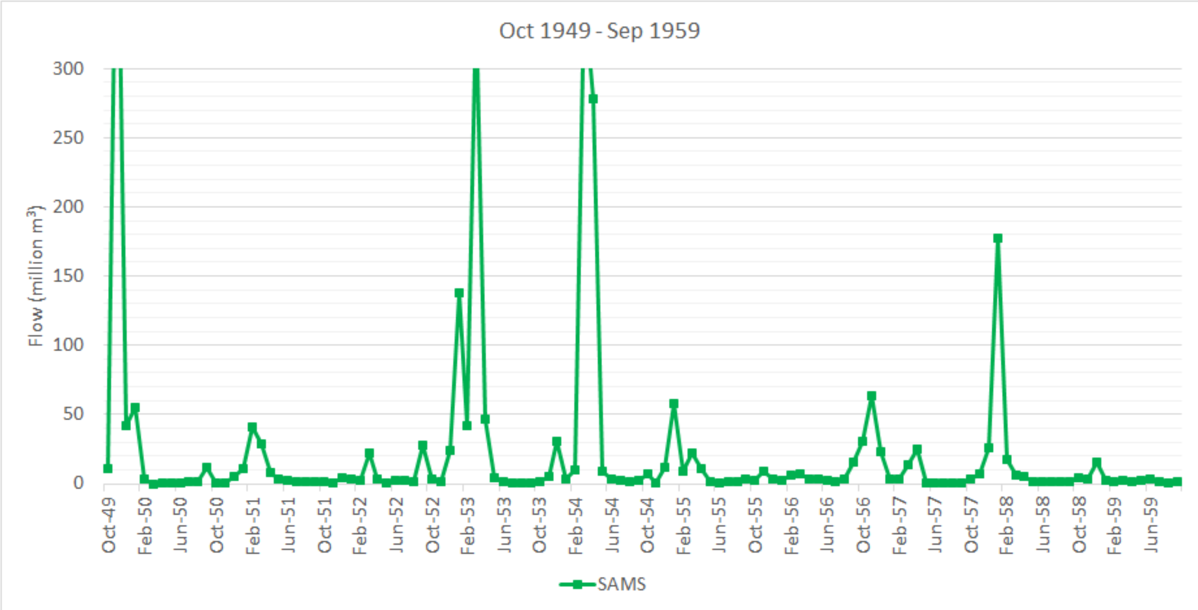

Figure C.4: SAMS generated streamflow data sequence 85 using a 3-parameter log-normal distribution

C.2 STOMSA

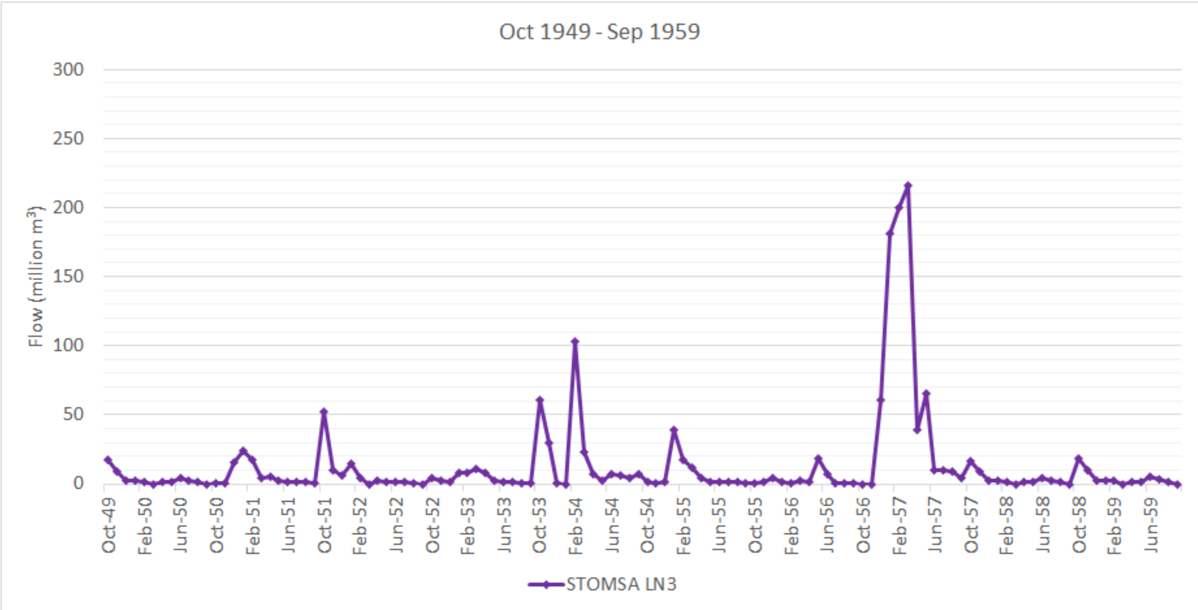

Figure C.5: STOMSA generated streamflow data sequence 28 using a 3-parameter log-normal distribution

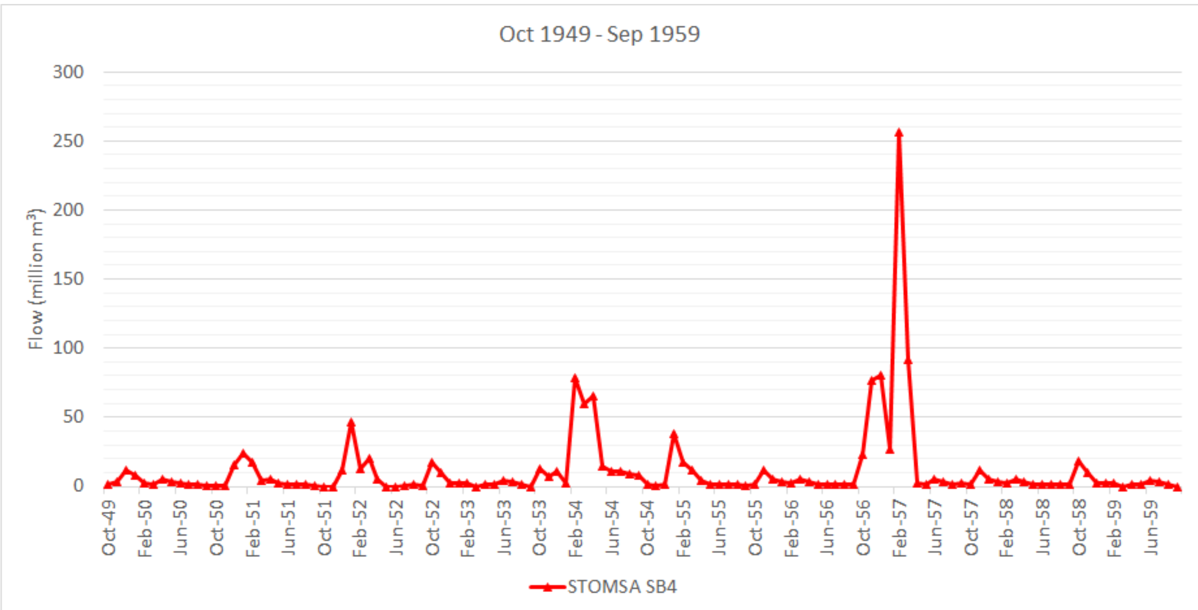

Figure C.6: STOMSA generated streamflow data sequence 28 using a 4-parameter bounded distribution

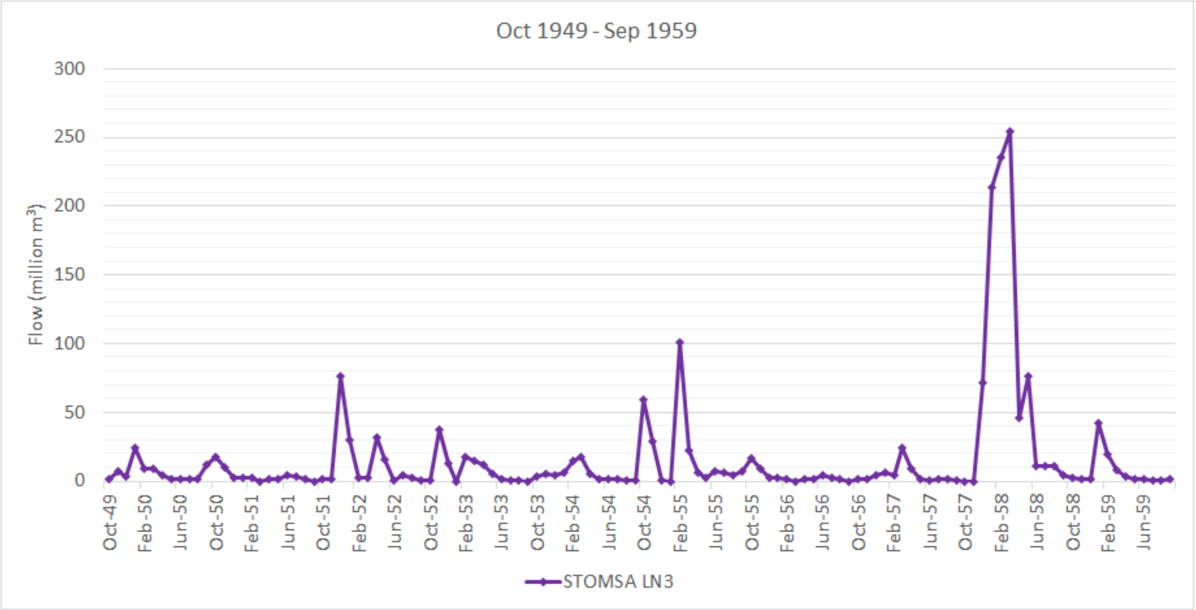

Figure C.7: STOMSA generated streamflow data sequence 40 using a 3-parameter log-normal distribution

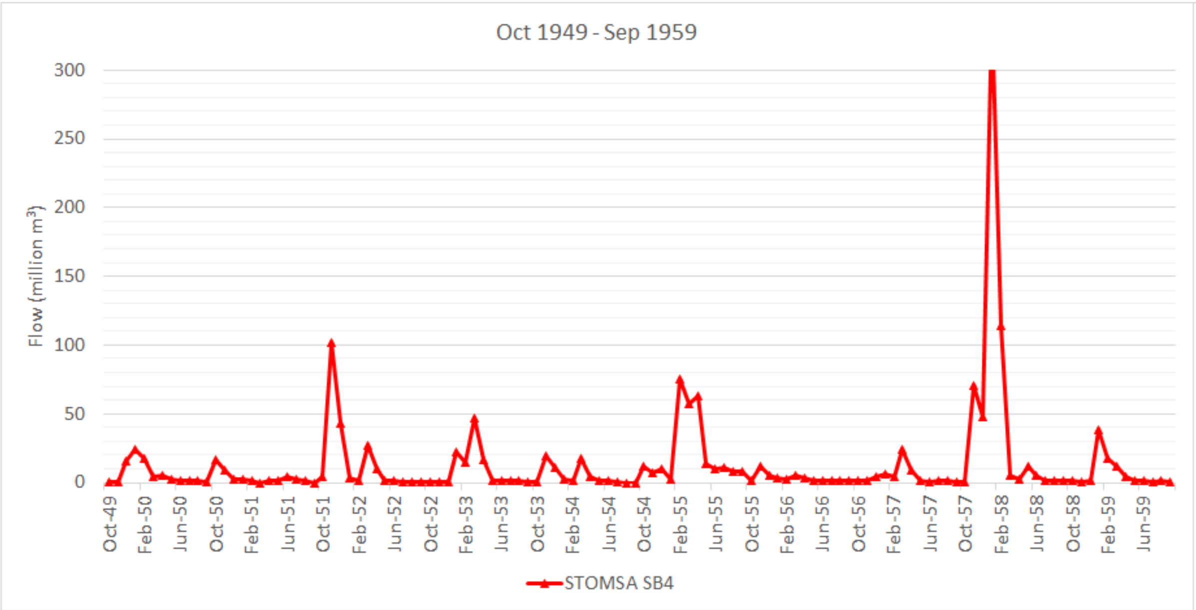

Figure C.8: STOMSA generated streamflow data sequence 40 using a 4-parameter bounded distribution

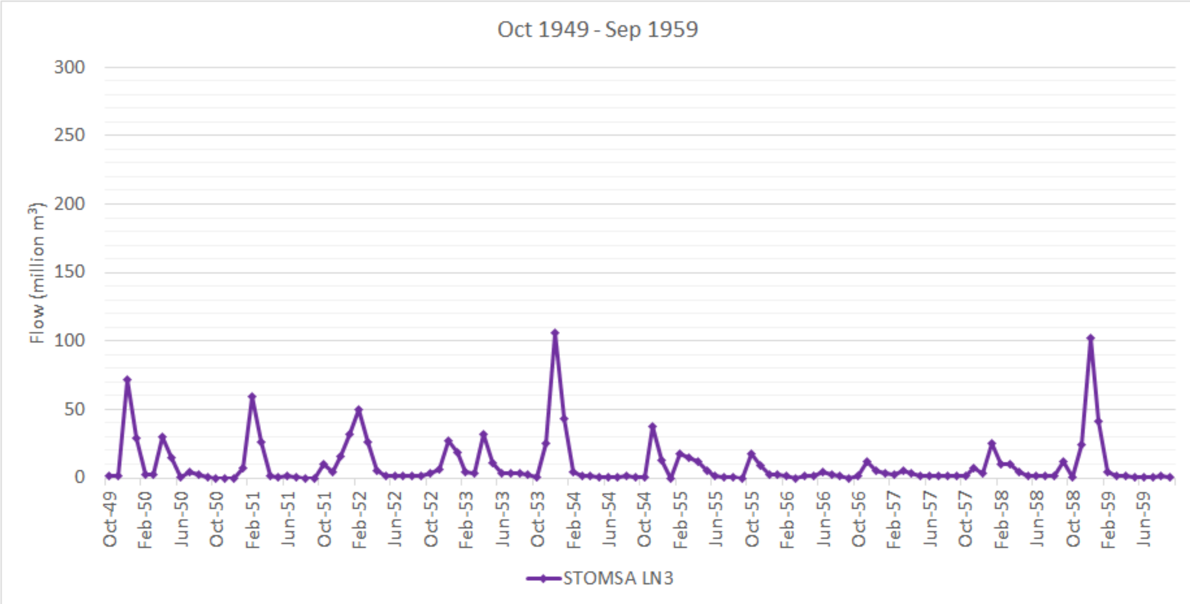

Figure C.9: STOMSA generated streamflow data sequence 63 using a 3-parameter log-normal distribution

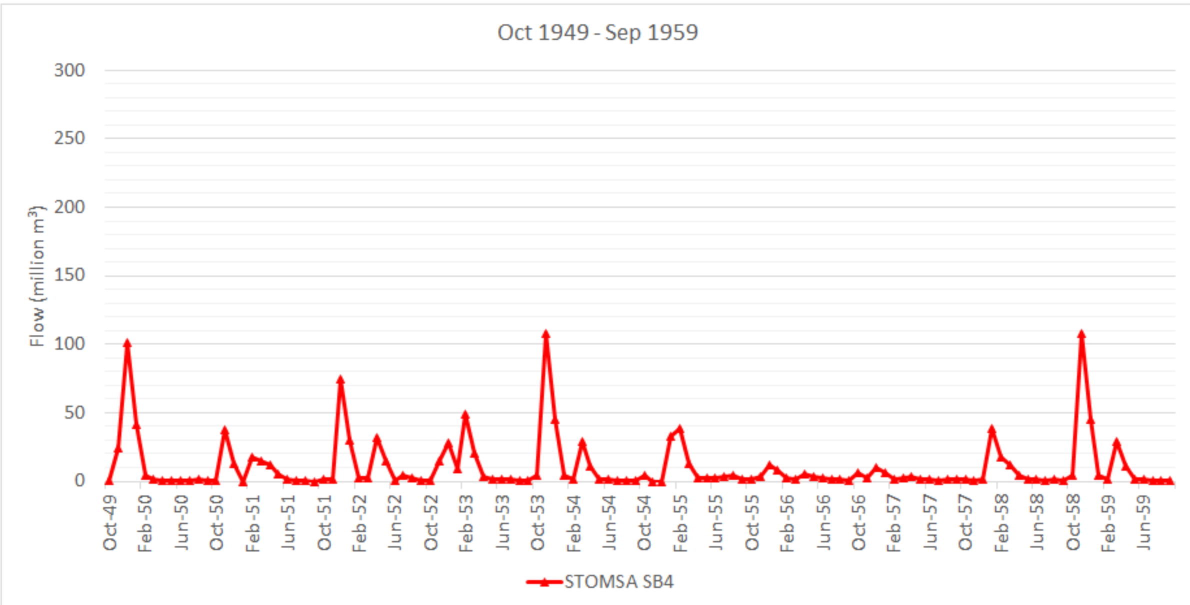

Figure C.10: STOMSA generated streamflow data sequence 63 using a 4-parameter bounded distribution

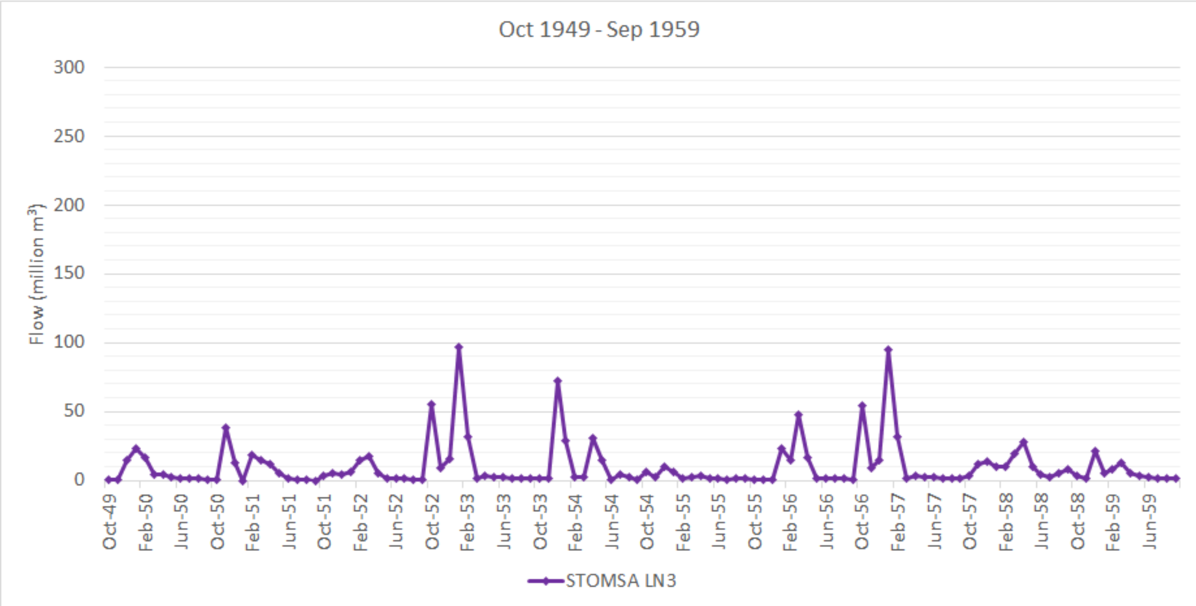

Figure C.11: STOMSA generated streamflow data sequence 85 using a 3-parameter log-normal distribution

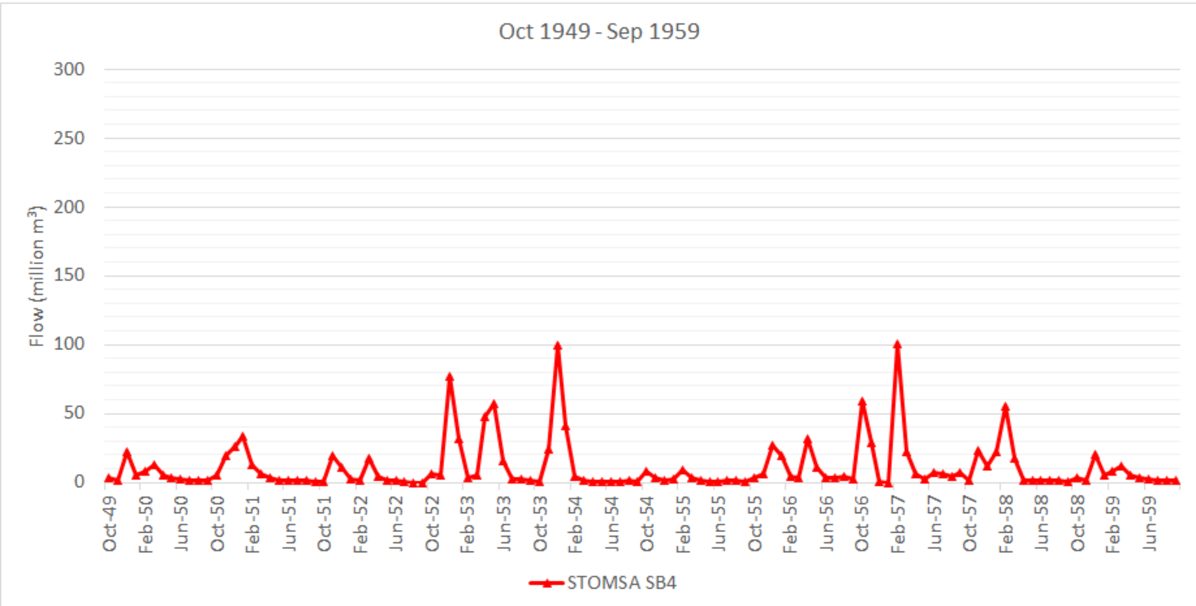

Figure C.12: STOMSA generated streamflow data sequence 85 using a 4-parameter bounded distribution

C.3 Generated Stochasic Streamflow Comparison

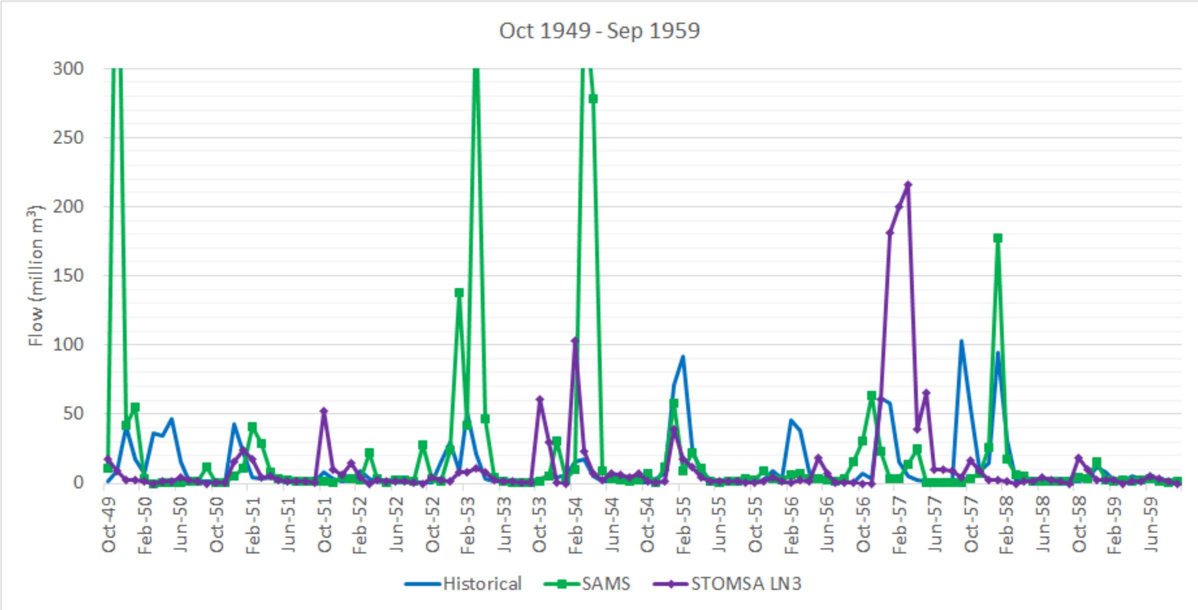

Figure C.13: Generated stochastic streamflow sequence 28 and historical streamflow sequence

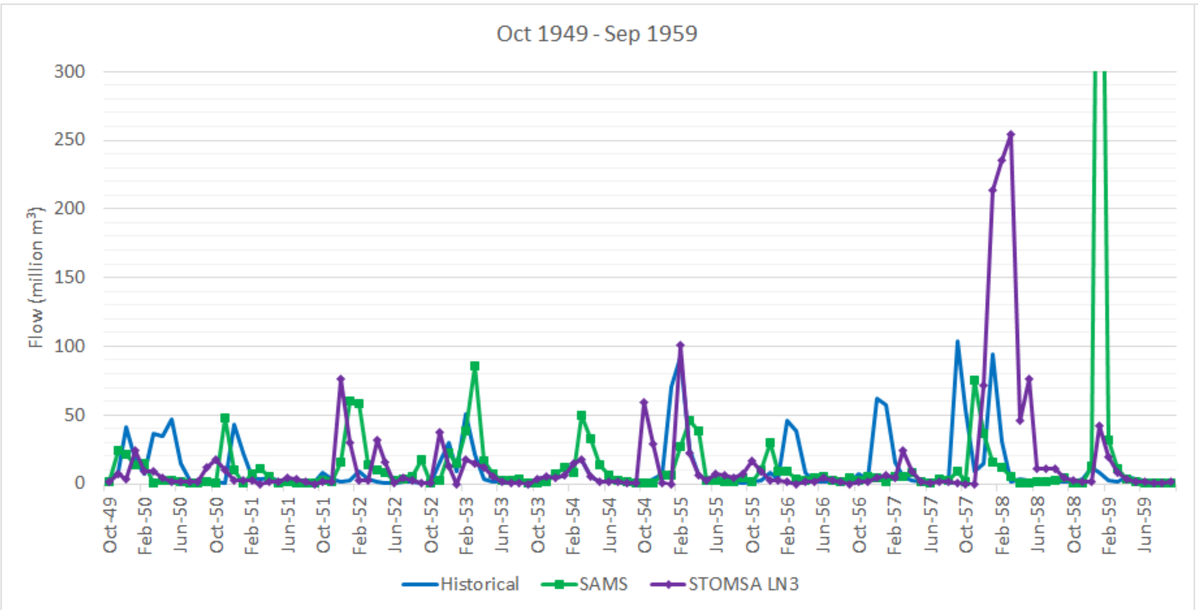

Figure C.14: Generated stochastic streamflow sequence 40 and historical streamflow sequence

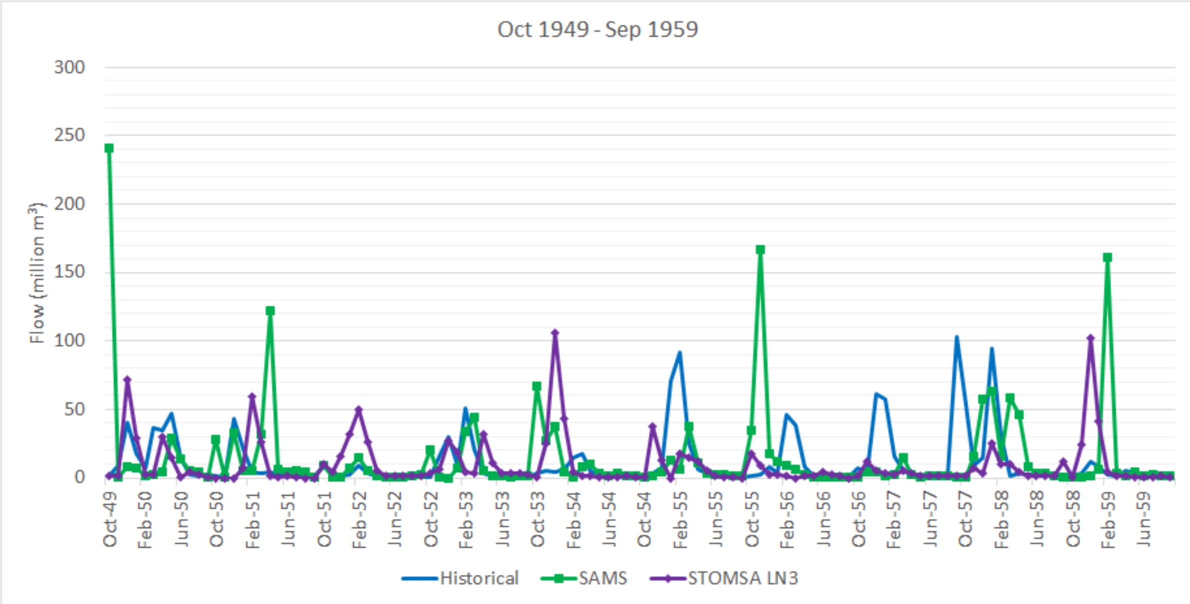

Figure C.15: Generated stochastic streamflow sequence 63 and historical streamflow sequence

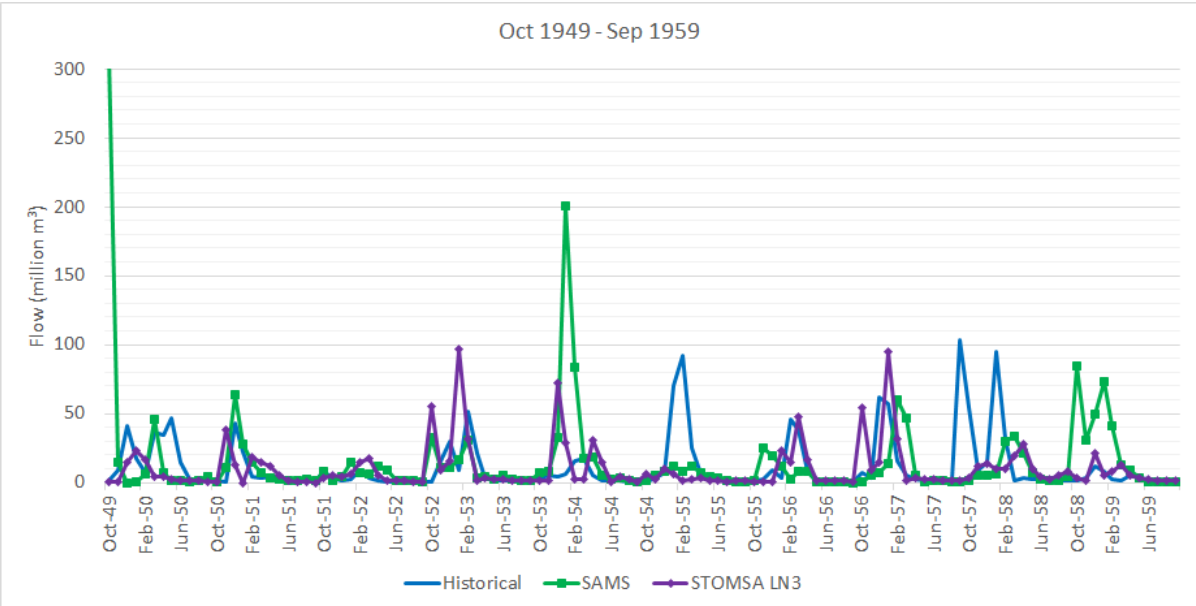

Figure C.16: Generated stochastic streamflow sequence 85 and historical streamflow sequence

C.4 Comparison with STOMSA SB4 Marginal Distribution

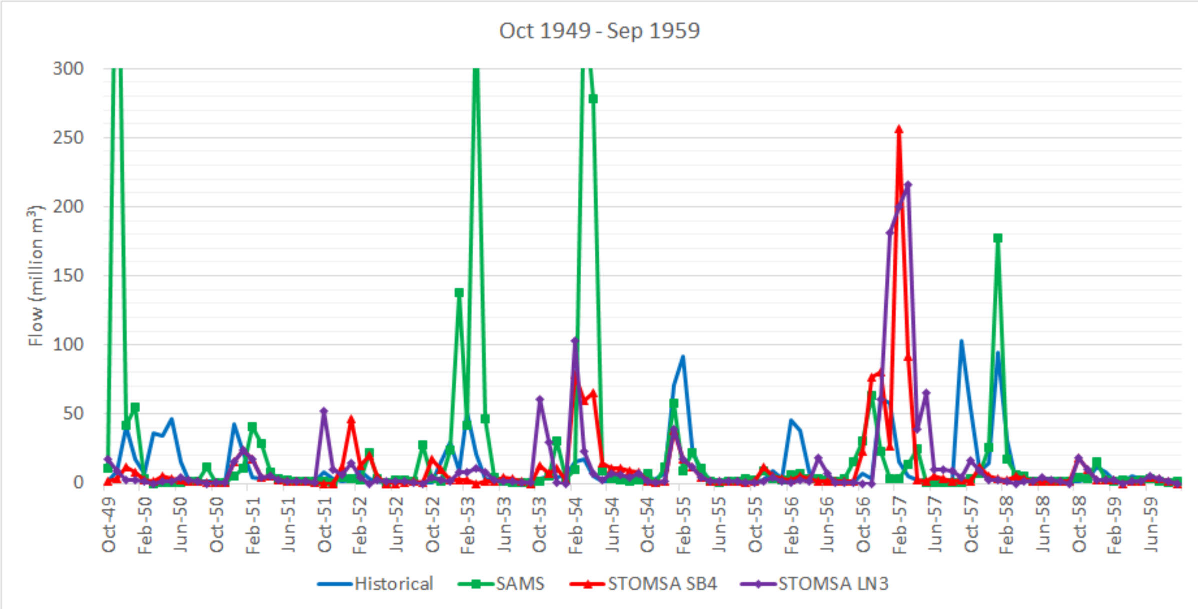

Figure C.17: Generated stochastic streamflow sequence 28 with STOMSA SB4 marginal distribution and historical streamflow sequence

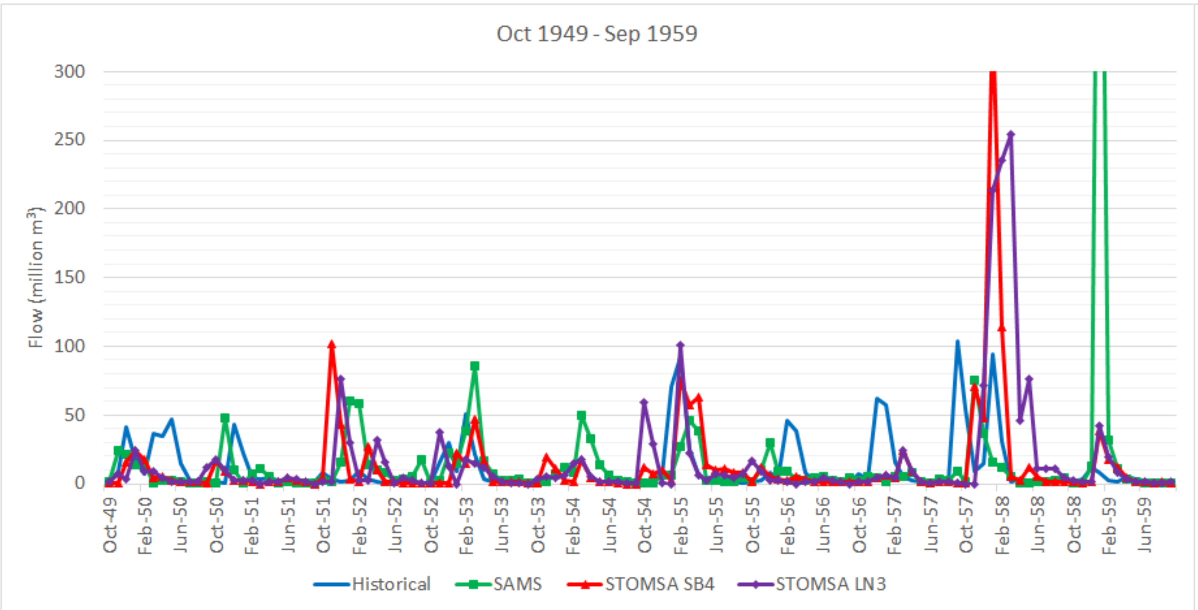

Figure C.18: Generated stochastic streamflow sequence 40 with STOMSA SB4 marginal distribution and historical streamflow sequence

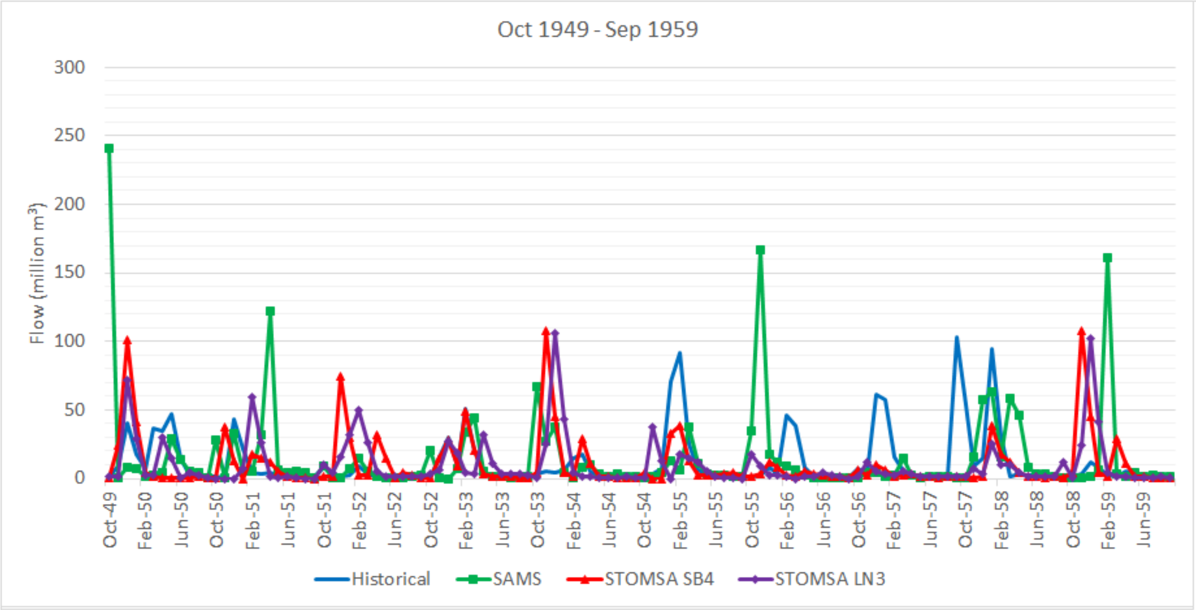

Figure C.19: Generated stochastic streamflow sequence 63 with STOMSA SB4 marginal distribution and historical streamflow sequence

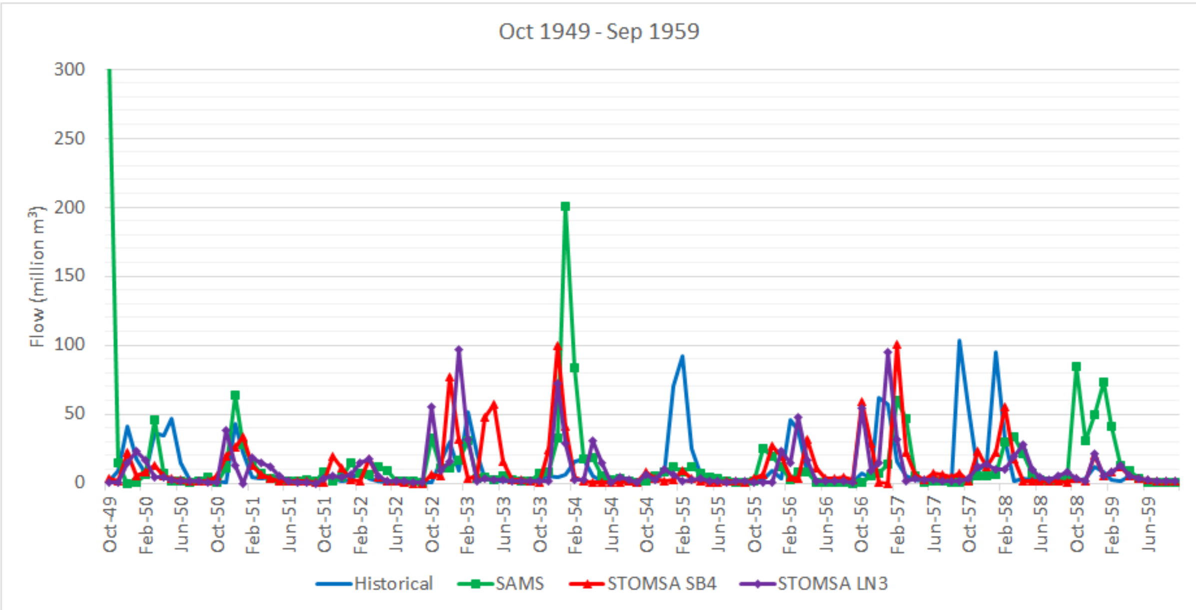

Figure C.20: Generated stochastic streamflow sequence 85 with STOMSA SB4 marginal distribution and historical streamflow sequence

Appendix D

Voëlvlei Dam Historical Files

D.1 Streamflow Data frm Flow Station G1R001 at Voëlvlei Dam

Table D.1: Historical streamflow data from flow station G1R001 (million m^3/s)

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	Total
1968	3.87	1.28	0.55	0.45	0.28	0.22	0.51	0.47	0.50	0.62	1.27	2.59	12.61
1969	2.45	0.86	0.52	0.33	0.25	0.22	0.14	0.54	1.74	2.64	3.65	1.99	15.33
1970	1.34	0.58	0.41	0.34	0.22	0.19	0.22	0.47	0.47	2.67	2.98	1.72	11.61
1971	1.22	0.55	0.37	0.26	0.18	0.14	0.19	0.29	3.31	2.96	2.26	1.04	12.77
1972	0.69	1.72	2.15	1.82	0.69	0.49	0.48	4.82	5.64	5.45	5.26	2.13	31.34
1973	1.13	0.55	0.52	0.28	0.22	0.24	0.42	0.90	0.50	0.22	1.06	2.03	8.07
1974	1.34	0.58	0.34	0.25	0.19	0.27	0.21	0.28	0.35	0.45	0.55	0.97	5.78
1975	2.36	0.86	0.34	0.37	0.29	0.19	0.25	0.78	1.07	0.77	1.19	1.04	9.51
1976	1.13	3.00	1.90	0.84	0.52	0.47	0.43	0.48	0.70	0.89	0.80	1.94	13.10
1977	1.09	0.59	0.40	0.55	0.42	0.52	0.72	0.85	1.94	2.37	0.79	0.47	10.71
1978	0.97	0.72	0.64	0.40	0.47	0.50	0.42	2.88	4.06	5.83	2.20	1.65	20.74
1979	1.18	0.56	0.43	0.30	0.24	0.31	0.35	3.90	1.46	3.22	1.90	3.78	17.63
1980	2.16	0.86	0.81	0.82	0.37	1.57	1.12	1.43	3.29	4.62	3.98	1.85	22.88
1981	1.26	0.61	0.42	0.30	0.19	0.33	0.38	0.87	1.73	2.93	5.60	2.66	17.28
1982	1.33	0.67	0.34	0.29	0.21	0.19	0.22	1.59	2.31	2.58	3.51	1.83	15.07
1983	1.21	0.57	0.41	0.30	0.19	0.20	0.76	0.65	3.13	2.30	1.60	2.61	13.93
1984	1.28	0.60	0.37	0.27	0.24	0.62	0.49	0.98	1.35	2.27	3.68	4.88	17.03
1985	1.73	0.92	0.54	0.37	0.30	0.23	0.58	1.59	1.90	4.72	2.95	1.01	16.84
1986	0.48	0.32	0.31	0.23	0.16	0.13	0.23	0.59	2.02	4.44	3.39	3.42	15.72
1987	1.86	1.12	0.57	0.37	0.37	0.35	0.69	1.01	4.59	4.07	2.45	2.39	19.84
1988	2.49	1.62	0.68	0.41	0.29	0.22	0.96	1.79	2.81	6.11	2.82	0.99	21.19
1989	0.56	0.33	0.31	0.22	0.16	0.14	0.24	0.26	2.99	3.50	1.34	1.09	11.14

1990	1.27	0.59	0.34	0.27	0.18	0.16	0.15	0.45	0.67	2.03	2.40	1.22	9.73
1991	2.21	1.33	0.72	0.40	0.31	0.27	0.39	0.39	2.96	3.75	3.78	5.67	22.18
1992	3.48	2.83	1.55	0.86	0.49	0.41	0.45	0.48	2.56	2.46	2.82	1.86	20.25
1993	0.74	0.65	0.53	0.35	0.26	0.19	0.20	1.02	1.43	1.75	1.75	0.98	9.85
1994	0.63	1.52	0.60	0.35	0.22	0.19	0.31	0.57	0.81	2.02	3.05	3.56	13.83
1995	1.75	0.67	0.39	0.29	0.21	0.19	0.13	0.40	0.57	1.28	1.50	2.58	9.96
1996	0.96	0.46	0.29	0.23	0.22	0.13	0.15	0.73	0.79	5.49	3.40	4.56	17.41
1997	1.48	0.89	0.50	0.59	0.32	0.26	0.29	1.08	1.44	3.15	3.78	1.58	15.36
1998	1.45	0.76	0.42	0.32	0.21	0.24	0.25	0.30	0.27	0.30	1.74	1.96	8.22
1999	1.12	0.67	0.48	0.32	0.19	0.17	0.33	0.22	0.52	0.80	2.57	0.91	8.30
2000	0.76	0.43	0.28	0.18	0.14	0.14	0.39	0.45	2.16	2.34	3.62	2.29	13.18
2001	1.04	0.69	0.39	0.24	0.16	0.15	0.39	1.80	2.07	1.17	2.15	1.05	11.30
2002	0.83	1.88	0.60	0.36	0.27	0.28	0.40	1.00	5.17	3.08	3.98	2.12	19.97

D.2 Historical Rainfall Distribution as a Percentage of the MAP of Rainfall Zone G1B

Table D.2: Historical rainfall distribution of rainfall zone G1B as a percentage of the MAP

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
1968	19.28	2.74	1.82	4.09	2.17	2.4	9.5	2.28	9.78	6.35	12.46	9.83
1969	10.78	1.11	0.32	0.43	1.86	0.42	0.74	11.2	24.07	15.16	14.25	7.91
1970	4.43	2.72	2.4	1.51	0.71	6.1	1.8	5.39	9.27	13.77	15.09	1.65
1971	2.48	1.22	2.11	3.63	2.55	3.33	12.44	13.53	11.96	11	6.15	6.2
1972	3.85	0	9.83	0.09	0.37	8.17	1.1	8.66	2.79	27.77	11.79	9.99
1973	4.91	2.41	7.23	0.94	1.32	1.63	1.89	25.79	23.46	9.85	46.37	9.05
1974	12.4	3.6	1.4	3.55	1.39	1.15	8.64	25.84	7.04	15.62	10.38	1.73
1975	9.77	3.29	1.32	0.47	1.03	2.4	15.72	6.68	34.82	14.78	7.9	6.44
1976	3.67	18.67	10.19	2.81	4.78	4.37	12.86	27.78	25.59	23.92	18.29	9.05
1977	4.12	3.95	5.02	2.34	2.08	6.71	8.49	5.97	2.54	1.45	19.03	10.2
1978	3.56	0.78	8.54	3.29	9.19	1.31	1.64	16.79	13.43	8.76	8.99	9.97
1979	9.89	1.59	0.12	5.87	3.22	0.24	7.2	16.28	13.37	3.42	11.95	3.23
1980	4.58	22.36	7.1	11.68	0.59	4.76	6.28	3.55	9.08	22.5	19.17	17.35
1981	3.89	2.1	3.01	7.01	0.56	6.33	18.24	9.42	16.38	9.17	7.4	1.65
1982	10.62	2.74	6.76	1.61	9.12	5.43	2.39	26.2	21.21	12.94	5.71	9.11
1983	2.43	4.57	2.65	1.67	0.31	13.48	5.65	33.66	5.14	10.96	5.11	17.32
1984	12.18	0.15	13.18	7.58	6.66	15.47	11.25	8.93	17.81	21.31	13.89	8.44

1985	0.99	0.84	3.24	1.69	1.85	7.04	6.72	7.64	19.11	16.15	21.28	8.09
1986	2.43	2.41	1.45	4.56	2.03	2.62	9.16	18.08	17.88	17.89	15.98	9.87
1987	1.52	1.15	5.65	0.15	1.54	2.69	15.62	7.68	13.62	11.22	15.93	10.72
1988	2.12	1.92	1.83	1.22	5.03	14.89	11.1	10.4	13.97	16.69	18.54	14.73
1989	7.22	7.09	0.32	2.3	5.12	0.78	22.35	17.63	19.2	18.87	7.88	2.34
1990	0.32	3.72	6.15	1.17	2.65	0.94	4.95	9.84	24.74	44.37	5.51	12.82
1991	9.11	2.29	2.19	0.03	5.81	4.35	8.14	11.46	26.27	16.3	12.59	7.53
1992	14.54	2.93	0.6	1.34	4.26	1.09	22.32	21.15	14.88	22.74	8.85	3.01
1993	0.51	1.14	3.07	1.59	0.38	1.76	11.86	5.74	31.69	8.71	3.95	11.53
1994	5.71	1.02	0.88	0.94	0.61	4.25	2.73	15.12	15.16	22.87	16.82	2.73
1995	12.41	1.63	11.51	1.26	6.86	4.85	4.73	9.28	19.51	15	20.07	19.09
1996	6.75	12.62	10.34	1.43	0.03	2.1	2.64	9.82	28.73	5.68	10.72	1.01
1997	1.51	7.1	5.25	6.22	0	1.96	3.98	21.52	9.44	11.74	8.06	3.55
1998	4.15	9.53	8.57	0.15	0.44	0.22	9.87	12.07	14.11	12.88	21.07	17.42
1999	0.27	2.46	3.16	3.8	0.02	1.67	1.05	6.45	10.1	17.06	11.11	16.97
2000	0.96	6.18	0.72	2.28	1.63	0.16	5.48	16.56	6.17	35.37	18.11	14.57
2001	8.54	5.26	1.3	11.1	4.16	2.12	9.2	20.31	12.3	18.19	16.78	6.06
2002	6.72	3.26	2.75	2.52	0.99	6.01	7.08	5.73	2.39	5.3	26.69	8.65

D.3 Historical Rainfall Data file of Rainfall Zone G1B

Table D.3: Historical rainfall data of rainfall zone G1B (mm)

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Total
1968	91.58	13.02	8.65	19.43	10.31	11.40	45.13	10.83	46.46	30.16	59.19	46.69	392.83
1969	51.21	5.27	1.52	2.04	8.84	2.00	3.52	53.20	114.33	72.01	67.69	37.57	419.19
1970	21.04	12.92	11.40	7.17	3.37	28.98	8.55	25.60	44.03	65.41	71.68	7.84	307.99
1971	11.78	5.80	10.02	17.24	12.11	15.82	59.09	64.27	56.81	52.25	29.21	29.45	363.85
1972	18.29	0.00	46.69	0.43	1.76	38.81	5.23	41.14	13.25	131.91	56.00	47.45	400.95
1973	23.32	11.45	34.34	4.47	6.27	7.74	8.98	122.50	111.44	46.79	220.26	42.99	640.54
1974	58.90	17.10	6.65	16.86	6.60	5.46	41.04	122.74	33.44	74.20	49.31	8.22	440.52
1975	46.41	15.63	6.27	2.23	4.89	11.40	74.67	31.73	165.40	70.21	37.53	30.59	496.95
1976	17.43	88.68	48.40	13.35	22.71	20.76	61.09	131.96	121.55	113.62	86.88	42.99	769.41
1977	19.57	18.76	23.85	11.12	9.88	31.87	40.33	28.36	12.07	6.89	90.39	48.45	341.53
1978	16.91	3.71	40.57	15.63	43.65	6.22	7.79	79.75	63.79	41.61	42.70	47.36	409.69
1979	46.98	7.55	0.57	27.88	15.30	1.14	34.20	77.33	63.51	16.25	56.76	15.34	362.81
1980	21.76	106.21	33.73	55.48	2.80	22.61	29.83	16.86	43.13	106.88	91.06	82.41	612.75

1981	18.48	9.98	14.30	33.30	2.66	30.07	86.64	44.75	77.81	43.56	35.15	7.84	404.51
1982	50.45	13.02	32.11	7.65	43.32	25.79	11.35	124.45	100.75	61.47	27.12	43.27	540.74
1983	11.54	21.71	12.59	7.93	1.47	64.03	26.84	159.89	24.42	52.06	24.27	82.27	489.01
1984	57.86	0.71	62.61	36.01	31.64	73.48	53.44	42.42	84.60	101.22	65.98	40.09	650.04
1985	4.70	3.99	15.39	8.03	8.79	33.44	31.92	36.29	90.77	76.71	101.08	38.43	449.54
1986	11.54	11.45	6.89	21.66	9.64	12.45	43.51	85.88	84.93	84.98	75.91	46.88	495.71
1987	7.22	5.46	26.84	0.71	7.32	12.78	74.20	36.48	64.70	53.30	75.67	50.92	415.58
1988	10.07	9.12	8.69	5.80	23.89	70.73	52.73	49.40	66.36	79.28	88.07	69.97	534.09
1989	34.30	33.68	1.52	10.93	24.32	3.71	106.16	83.74	91.20	89.63	37.43	11.12	527.73
1990	1.52	17.67	29.21	5.56	12.59	4.47	23.51	46.74	117.52	210.76	26.17	60.90	556.61
1991	43.27	10.88	10.40	0.14	27.60	20.66	38.67	54.44	124.78	77.43	59.80	35.77	503.83
1992	69.07	13.92	2.85	6.37	20.24	5.18	106.02	100.46	70.68	108.02	42.04	14.30	559.12
1993	2.42	5.42	14.58	7.55	1.81	8.36	56.34	27.27	150.53	41.37	18.76	54.77	389.17
1994	27.12	4.85	4.18	4.47	2.90	20.19	12.97	71.82	72.01	108.63	79.90	12.97	421.99
1995	58.95	7.74	54.67	5.99	32.59	23.04	22.47	44.08	92.67	71.25	95.33	90.68	599.45
1996	32.06	59.95	49.12	6.79	0.14	9.98	12.54	46.65	136.47	26.98	50.92	4.80	436.38
1997	7.17	33.73	24.94	29.55	0.00	9.31	18.91	102.22	44.84	55.77	38.29	16.86	381.57
1998	19.71	45.27	40.71	0.71	2.09	1.05	46.88	57.33	67.02	61.18	100.08	82.75	524.78
1999	1.28	11.69	15.01	18.05	0.10	7.93	4.99	30.64	47.98	81.04	52.77	80.61	352.07
2000	4.56	29.36	3.42	10.83	7.74	0.76	26.03	78.66	29.31	168.01	86.02	69.21	513.90
2001	40.57	24.99	6.18	52.73	19.76	10.07	43.70	96.47	58.43	86.40	79.71	28.79	547.77
2002	31.92	15.49	13.06	11.97	4.70	28.55	33.63	27.22	11.35	25.18	126.78	41.09	370.93

Appendix E

Parameter File of Flow Station G1R001

1 PARAMETER FILE

1 1

C:\Tulbagh \Hydro \FlowA
35 1968 1.0044 1.0044 -0.5903 -0.5903
1 -7.3812880 2.8006301 1.0000000 0.0000000
0.00000 1.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0
14.84743 5.25169 18.56061 37.12121 1.000

B - THE SQUARE-ROOT OF THE LAG-ZERO DISPERSION MATRIX G0
-1.00000000

B0 - THE SQUARE-ROOT OF THE LAG-ZERO STARTING MATRIX H0
0.00000000

B1 - THE SQUARE-ROOT OF THE LAG-ONE STARTING MATRIX H1
0.00000000

A - THE COEFFICIENT MATRIX OF Z(-1) IN CALCULATING Z(0)
0.00000000

C - THE COEFFICIENT MATRIX OF A(-1) IN CALCULATING Z(0)
0.00000000

Appendix F

WRYM Failure Sequences

F.1 Without Gains and Losses

Table F.1: WRYM number of failures per sequence without gains and losses

Sequence	Number of failures	Sequence	Number of failures	Sequence	Number of failures	Sequence	Number of failures	Sequence	Number of failures
1	1	41	2	81	0	121	0	161	0
2	0	42	0	82	1	122	0	162	0
3	0	43	1	83	0	123	0	163	0
4	0	44	1	84	0	124	2	164	2
5	1	45	1	85	2	125	0	165	0
6	0	46	0	86	1	126	0	166	1
7	1	47	0	87	0	127	1	167	0
8	0	48	0	88	0	128	0	168	1
9	1	49	0	89	0	129	0	169	1
10	0	50	0	90	2	130	0	170	1
11	2	51	0	91	1	131	0	171	1
12	1	52	0	92	1	132	0	172	0
13	2	53	1	93	0	133	2	173	0
14	0	54	0	94	0	134	0	174	0
15	0	55	1	95	0	135	0	175	0
16	1	56	1	96	1	136	0	176	1
17	0	57	1	97	1	137	0	177	0
18	0	58	1	98	1	138	2	178	0
19	0	59	0	99	0	139	0	179	0
20	0	60	0	100	2	140	0	180	0
21	0	61	2	101	1	141	1	181	1

22	0	62	0	102	0	142	0	182	0
23	0	63	1	103	0	143	1	183	1
24	1	64	0	104	0	144	0	184	0
25	1	65	0	105	0	145	0	185	0
26	2	66	0	106	1	146	0	186	1
27	0	67	2	107	0	147	0	187	0
28	0	68	3	108	1	148	1	188	0
29	1	69	1	109	0	149	0	189	0
30	2	70	0	110	0	150	0	190	1
31	1	71	0	111	0	151	0	191	0
32	0	72	0	112	1	152	2	192	1
33	0	73	0	113	1	153	1	193	0
34	0	74	2	114	2	154	1	194	1
35	1	75	2	115	0	155	0	195	0
36	0	76	0	116	0	156	0	196	0
37	0	77	0	117	0	157	0	197	0
38	0	78	0	118	0	158	0	198	1
39	0	79	0	119	1	159	0	199	0
40	1	80	0	120	1	160	0	200	1
								201	0
Total failed sequences				75					
Sequences failing more than once				19					

F.2 With Gains and Losses

Table F.2: WRYM number of failures per sequence with gains and losses

Sequence	Number of failures	Sequence	Number of failures	Sequence	Number of failures	Sequence	Number of failures	Sequence	Number of failures
1	1	41	2	81	1	121	0	161	0
2	0	42	0	82	3	122	0	162	1
3	0	43	1	83	0	123	0	163	1
4	0	44	1	84	0	124	2	164	2
5	3	45	1	85	2	125	0	165	1
6	0	46	0	86	3	126	0	166	1
7	1	47	0	87	1	127	1	167	0
8	0	48	0	88	0	128	1	168	1

9	1	49	0	89	0	129	0	169	1
10	0	50	0	90	2	130	0	170	2
11	2	51	0	91	1	131	1	171	1
12	0	52	0	92	1	132	0	172	1
13	2	53	1	93	0	133	2	173	1
14	0	54	0	94	1	134	1	174	0
15	2	55	1	95	0	135	1	175	0
16	2	56	1	96	1	136	0	176	1
17	0	57	2	97	2	137	0	177	0
18	0	58	1	98	0	138	2	178	0
19	0	59	0	99	0	139	0	179	0
20	0	60	0	100	2	140	0	180	0
21	0	61	3	101	1	141	1	181	1
22	0	62	0	102	0	142	0	182	1
23	0	63	1	103	0	143	1	183	1
24	2	64	0	104	0	144	0	184	0
25	1	65	0	105	0	145	0	185	0
26	3	66	0	106	2	146	0	186	1
27	1	67	3	107	0	147	1	187	0
28	0	68	3	108	1	148	1	188	0
29	1	69	1	109	1	149	0	189	1
30	2	70	0	110	0	150	0	190	2
31	2	71	0	111	0	151	0	191	0
32	0	72	1	112	1	152	2	192	1
33	0	73	2	113	1	153	1	193	0
34	0	74	2	114	2	154	1	194	2
35	1	75	2	115	1	155	0	195	0
36	0	76	0	116	0	156	1	196	0
37	0	77	0	117	0	157	0	197	0
38	0	78	0	118	0	158	0	198	2
39	0	79	0	119	1	159	0	199	0
40	2	80	0	120	1	160	0	200	1
								201	0
Total failed sequences				95					
Sequences failing more than once				35					

Appendix G

WRYM Own Calculations

G.1 Ranked Base Yields without Gains and Losses

Table G.1: WRYM ranked base yields without gains and losses

Rank	Plotting Position	Base Yield ($million\ m^3$)	Rank	Plotting Position	Base Yield ($million\ m^3$)
1	0.50%	5.07	168	83.58%	5.06
...	...	...	169	84.08%	5.05
135	67.16%	5.07	170	84.58%	5.05
136	67.66%	5.06	171	85.07%	5.05
137	68.16%	5.06	172	85.57%	5.05
138	68.66%	5.06	173	86.07%	5.05
139	69.15%	5.06	174	86.57%	5.05
140	69.65%	5.06	175	87.06%	5.05
141	70.15%	5.06	176	87.56%	5.05
142	70.65%	5.06	177	88.06%	5.05
143	71.14%	5.06	178	88.56%	5.05
144	71.64%	5.06	179	89.05%	5.05
145	72.14%	5.06	180	89.55%	5.05
146	72.64%	5.06	181	90.05%	5.05
147	73.13%	5.06	182	90.55%	5.05
148	73.63%	5.06	183	91.04%	5.04
149	74.13%	5.06	184	91.54%	5.02
150	74.63%	5.06	185	92.04%	5.01
151	75.12%	5.06	186	92.54%	4.99
152	75.62%	5.06	187	93.03%	4.99
153	76.12%	5.06	188	93.53%	4.99

154	76.62%	5.06	189	94.03%	4.98
155	77.11%	5.06	190	94.53%	4.92
156	77.61%	5.06	191	95.02%	4.92
157	78.11%	5.06	192	95.52%	4.90
158	78.61%	5.06	193	96.02%	4.88
159	79.10%	5.06	194	96.52%	4.87
160	79.60%	5.06	195	97.01%	4.84
161	80.10%	5.06	196	97.51%	4.75
162	80.60%	5.06	197	98.01%	4.75
163	81.09%	5.06	198	98.51%	4.67
164	81.59%	5.06	199	99.00%	4.63
165	82.09%	5.06	200	99.50%	4.59
166	82.59%	5.06	201	100.00%	4.35
167	83.08%	5.06			

G.2 Ranked Base Yields with Gains and Losses

Table G.2: WRYM ranked base yields with gains and losses

Rank	Plotting Position	Base Yield ($million\ m^3$)	Rank	Plotting Position	Base Yield ($million\ m^3$)
1	0.50%	4.78	153	76.12%	4.76
...	...	...	154	76.62%	4.76
106	52.74%	4.78	155	77.11%	4.76
107	53.23%	4.78	156	77.61%	4.76
108	53.73%	4.78	157	78.11%	4.76
109	54.23%	4.78	158	78.61%	4.76
110	54.73%	4.78	159	79.10%	4.76
111	55.22%	4.78	160	79.60%	4.76
112	55.72%	4.78	161	80.10%	4.76
113	56.22%	4.78	162	80.60%	4.76
114	56.72%	4.78	163	81.09%	4.76
115	57.21%	4.78	164	81.59%	4.76
116	57.71%	4.77	165	82.09%	4.76
117	58.21%	4.77	166	82.59%	4.76
118	58.71%	4.77	167	83.08%	4.76
119	59.20%	4.77	168	83.58%	4.76

120	59.70%	4.77	169	84.08%	4.76
121	60.20%	4.77	170	84.58%	4.76
122	60.70%	4.77	171	85.07%	4.76
123	61.19%	4.77	172	85.57%	4.76
124	61.69%	4.77	173	86.07%	4.76
125	62.19%	4.77	174	86.57%	4.76
126	62.69%	4.77	175	87.06%	4.76
127	63.18%	4.77	176	87.56%	4.76
128	63.68%	4.77	177	88.06%	4.76
129	64.18%	4.77	178	88.56%	4.75
130	64.68%	4.77	179	89.05%	4.75
131	65.17%	4.77	180	89.55%	4.75
132	65.67%	4.77	181	90.05%	4.75
133	66.17%	4.77	182	90.55%	4.75
134	66.67%	4.77	183	91.04%	4.75
135	67.16%	4.77	184	91.54%	4.75
136	67.66%	4.77	185	92.04%	4.75
137	68.16%	4.77	186	92.54%	4.74
138	68.66%	4.77	187	93.03%	4.74
139	69.15%	4.77	188	93.53%	4.74
140	69.65%	4.76	189	94.03%	4.73
141	70.15%	4.76	190	94.53%	4.70
142	70.65%	4.76	191	95.02%	4.67
143	71.14%	4.76	192	95.52%	4.65
144	71.64%	4.76	193	96.02%	4.63
145	72.14%	4.76	194	96.52%	4.62
146	72.64%	4.76	195	97.01%	4.59
147	73.13%	4.76	196	97.51%	4.57
148	73.63%	4.76	197	98.01%	4.52
149	74.13%	4.76	198	98.51%	4.44
150	74.63%	4.76	199	99.00%	4.40
151	75.12%	4.76	200	99.50%	4.36
152	75.62%	4.76	201	100.00%	4.26

Appendix H

MIKE Hydro Basin Calculations

H.1 Ranked Base Yields without Gains and Losses

Table H.1: MIKE Hydro Basin ranked base yields without gains and losses

Rank	Plotting Position	Base Yield ($million\ m^3$)	Rank	Plotting Position	Base Yield ($million\ m^3$)
1	0.50%	5.07	162	80.60%	5.06
...	...	...	163	81.09%	5.06
123	61.19%	5.07	164	81.59%	5.06
124	61.69%	5.07	165	82.09%	5.06
125	62.19%	5.07	166	82.59%	5.06
126	62.69%	5.07	167	83.08%	5.06
127	63.18%	5.07	168	83.58%	5.06
128	63.68%	5.07	169	84.08%	5.06
129	64.18%	5.07	170	84.58%	5.05
130	64.68%	5.07	171	85.07%	5.05
131	65.17%	5.07	172	85.57%	5.05
132	65.67%	5.07	173	86.07%	5.05
133	66.17%	5.07	174	86.57%	5.05
134	66.67%	5.07	175	87.06%	5.05
135	67.16%	5.07	176	87.56%	5.05
136	67.66%	5.07	177	88.06%	5.05
137	68.16%	5.07	178	88.56%	5.05
138	68.66%	5.07	179	89.05%	5.05
139	69.15%	5.07	180	89.55%	5.05
140	69.65%	5.07	181	90.05%	5.05
141	70.15%	5.06	182	90.55%	5.05

142	70.65%	5.06	183	91.04%	5.04
143	71.14%	5.06	184	91.54%	5.02
144	71.64%	5.06	185	92.04%	5.01
145	72.14%	5.06	186	92.54%	5.00
146	72.64%	5.06	187	93.03%	5.00
147	73.13%	5.06	188	93.53%	4.99
148	73.63%	5.06	189	94.03%	4.98
149	74.13%	5.06	190	94.53%	4.92
150	74.63%	5.06	191	95.02%	4.92
151	75.12%	5.06	192	95.52%	4.91
152	75.62%	5.06	193	96.02%	4.89
153	76.12%	5.06	194	96.52%	4.88
154	76.62%	5.06	195	97.01%	4.83
155	77.11%	5.06	196	97.51%	4.76
156	77.61%	5.06	197	98.01%	4.75
157	78.11%	5.06	198	98.51%	4.67
158	78.61%	5.06	199	99.00%	4.63
159	79.10%	5.06	200	99.50%	4.59
160	79.60%	5.06	201	100.00%	4.35
161	80.10%	5.06			

H.2 Ranked Base Yields with Gains and Losses

Table H.2: MIKE Hydro Basin ranked base yields with gains and losses

Rank	Plotting Position	Base Yield ($million\ m^3$)	Rank	Plotting Position	Base Yield ($million\ m^3$)
1	0.50%	5.07	156	77.61%	4.76
...	...	...	157	78.11%	4.76
111	55.22%	4.78	158	78.61%	4.76
112	55.72%	4.78	159	79.10%	4.76
113	56.22%	4.78	160	79.60%	4.76
114	56.72%	4.78	161	80.10%	4.76
115	57.21%	4.78	162	80.60%	4.76
116	57.71%	4.78	163	81.09%	4.76
117	58.21%	4.78	164	81.59%	4.76
118	58.71%	4.77	165	82.09%	4.76

119	59.20%	4.77	166	82.59%	4.76
120	59.70%	4.77	167	83.08%	4.76
121	60.20%	4.77	168	83.58%	4.76
122	60.70%	4.77	169	84.08%	4.76
123	61.19%	4.77	170	84.58%	4.76
124	61.69%	4.77	171	85.07%	4.76
125	62.19%	4.77	172	85.57%	4.76
126	62.69%	4.77	173	86.07%	4.76
127	63.18%	4.77	174	86.57%	4.76
128	63.68%	4.77	175	87.06%	4.76
129	64.18%	4.77	176	87.56%	4.76
130	64.68%	4.77	177	88.06%	4.76
131	65.17%	4.77	178	88.56%	4.76
132	65.67%	4.77	179	89.05%	4.76
133	66.17%	4.77	180	89.55%	4.76
134	66.67%	4.77	181	90.05%	4.75
135	67.16%	4.77	182	90.55%	4.75
136	67.66%	4.77	183	91.04%	4.75
137	68.16%	4.77	184	91.54%	4.75
138	68.66%	4.77	185	92.04%	4.75
139	69.15%	4.77	186	92.54%	4.74
140	69.65%	4.77	187	93.03%	4.74
141	70.15%	4.77	188	93.53%	4.74
142	70.65%	4.77	189	94.03%	4.73
143	71.14%	4.77	190	94.53%	4.70
144	71.64%	4.77	191	95.02%	4.67
145	72.14%	4.77	192	95.52%	4.65
146	72.64%	4.76	193	96.02%	4.64
147	73.13%	4.76	194	96.52%	4.63
148	73.63%	4.76	195	97.01%	4.59
149	74.13%	4.76	196	97.51%	4.57
150	74.63%	4.76	197	98.01%	4.52
151	75.12%	4.76	198	98.51%	4.44
152	75.62%	4.76	199	99.00%	4.40
153	76.12%	4.76	200	99.50%	4.36
154	76.62%	4.76	201	100.00%	4.25
155	77.11%	4.76			

Appendix I

Stochastic Rainfall File

Table I.1: Stochastic sequence 1 rainfall data from Voëlvlei dam (mm)

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
1968	40.96	20.63	10.47	8.93	6.47	5.85	6.77	48.97	71.14	79.46	108.10	56.36
1969	39.31	18.52	13.32	9.75	6.17	6.50	24.69	21.12	101.70	74.73	51.99	84.80
1970	15.25	10.17	9.85	7.31	5.08	4.13	7.31	18.75	64.19	141.08	107.72	108.67
1971	15.48	10.32	10.00	7.42	5.16	4.19	7.42	19.03	65.14	143.18	109.32	110.28
1972	17.66	10.41	9.78	6.94	5.05	4.41	7.57	8.20	94.29	110.37	42.26	34.37
1973	120.55	39.87	17.13	14.02	8.72	6.85	15.89	14.64	15.58	19.31	39.56	80.68
1974	21.72	54.15	67.68	57.29	21.72	15.43	15.11	151.73	177.55	171.57	165.58	67.05
1975	69.30	27.59	25.99	26.31	11.87	50.37	35.93	45.88	105.55	148.22	127.69	59.35
1976	15.33	10.22	9.90	7.35	5.11	4.15	7.35	18.85	64.52	141.82	108.28	109.24
1977	19.84	47.86	18.89	11.02	6.93	5.98	9.76	17.95	25.50	63.60	96.04	112.09
1978	41.69	18.05	10.58	7.78	5.91	8.40	6.53	8.71	10.89	14.00	17.11	30.18
1979	47.79	28.74	16.14	19.05	10.33	8.39	9.36	34.87	46.49	101.71	122.05	51.01
1980	32.86	16.00	15.12	8.14	6.40	6.98	12.21	26.17	14.54	6.40	30.83	59.04
1981	55.35	29.43	17.28	11.84	9.60	7.36	18.55	50.87	60.78	151.00	94.38	32.31
1982	39.93	18.95	14.55	10.15	8.12	10.49	11.84	131.98	49.41	108.96	64.30	127.91
1983	15.57	10.38	10.06	7.46	5.19	4.22	7.46	19.14	65.53	144.04	109.98	110.95
1984	68.07	27.10	25.53	25.84	11.66	49.48	35.30	45.06	103.68	145.59	125.43	58.30
1985	47.41	28.51	16.02	18.90	10.25	8.33	9.29	34.60	46.13	100.91	121.09	50.61
1986	36.04	21.56	15.45	10.30	6.11	5.47	10.62	7.08	16.73	25.74	82.70	29.28
1987	46.28	24.26	13.40	10.21	6.70	7.66	7.98	9.57	8.62	9.57	55.53	62.55
1988	50.84	22.01	12.90	9.49	7.21	10.24	7.97	10.62	13.28	17.07	20.87	36.80
1989	58.62	35.30	17.96	11.66	11.66	11.03	21.75	31.83	144.66	128.28	77.22	75.33
1990	20.19	48.72	19.23	11.22	7.05	6.09	9.94	18.27	25.96	64.75	97.77	114.11
1991	44.18	19.12	13.52	11.21	7.25	6.26	7.25	15.50	15.50	88.03	98.25	56.71

1992	56.92	21.79	12.69	9.43	6.83	6.18	4.23	13.01	18.54	41.63	48.79	83.92
1993	123.06	40.70	17.49	14.31	8.90	7.00	16.22	14.95	15.90	19.72	40.39	82.36
1994	57.11	34.39	17.50	11.36	11.36	10.75	21.18	31.01	140.92	124.96	75.22	73.38
1995	121.71	40.26	17.30	14.15	8.81	6.92	16.04	14.78	15.72	19.50	39.94	81.45
1996	38.14	18.10	13.90	9.70	7.76	10.02	11.31	126.06	47.19	104.08	61.42	122.18
1997	77.93	27.36	16.54	10.50	7.95	7.00	4.45	17.18	55.35	83.98	116.10	63.30
1998	24.85	14.06	9.16	5.89	4.58	4.58	12.75	14.72	70.64	76.53	118.39	74.89
1999	56.27	21.54	12.54	9.32	6.75	6.11	4.18	12.86	18.33	41.16	48.23	82.96
2000	39.24	17.69	11.90	8.36	5.79	4.50	6.11	9.33	106.46	95.20	72.69	33.45
2001	41.61	20.96	10.64	9.07	6.57	5.94	6.88	49.75	72.27	80.72	109.82	57.25
2002	59.56	35.86	18.25	11.85	11.85	11.21	22.09	32.34	146.98	130.33	78.45	76.53

Appendix J

Evaporation and Precipitation for WRYM

J.1 WRYM Evaporation for Stochastic Sequence 1

Table J.1: Evaporation from reservoir surface for WRYM (m^3/s)

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
1968	0.01105	0.01588	0.01879	0.01731	0.01512	0.01011	0.00444	0.00158	0.00384	0.00330	0.00457	0.00708
1969	0.01105	0.01588	0.01879	0.01864	0.01681	0.01136	0.00538	0.00455	0.00379	0.00330	0.00457	0.00708
1970	0.01105	0.01588	0.01715	0.01542	0.01248	0.00743	0.00235	0.00054	0.00089	0.00330	0.00457	0.00708
1971	0.01105	0.01588	0.01722	0.01555	0.01267	0.00761	0.00248	0.00062	0.00097	0.00330	0.00457	0.00708
1972	0.01105	0.01588	0.01726	0.01549	0.01238	0.00733	0.00236	0.00058	0.00000	0.00330	0.00457	0.00708
1973	0.01105	0.01588	0.01879	0.01917	0.01936	0.01444	0.00737	0.00440	0.00308	0.00288	0.00457	0.00708
1974	0.01105	0.01588	0.01879	0.01917	0.01959	0.01643	0.01048	0.00571	0.00384	0.00330	0.00457	0.00708
1975	0.01105	0.01588	0.01879	0.01917	0.01959	0.01588	0.01048	0.00571	0.00384	0.00330	0.00457	0.00708
1976	0.01105	0.01588	0.01718	0.01546	0.01255	0.00749	0.00240	0.00057	0.00092	0.00330	0.00457	0.00708
1977	0.01105	0.01588	0.01879	0.01917	0.01794	0.01257	0.00600	0.00282	0.00234	0.00303	0.00457	0.00708
1978	0.01105	0.01588	0.01879	0.01736	0.01462	0.00949	0.00470	0.00169	0.00073	0.00049	0.00079	0.00192
1979	0.00765	0.01588	0.01879	0.01917	0.01959	0.01527	0.00827	0.00398	0.00384	0.00330	0.00457	0.00708
1980	0.01105	0.01588	0.01879	0.01917	0.01657	0.01126	0.00544	0.00286	0.00313	0.00283	0.00318	0.00708
1981	0.01105	0.01588	0.01879	0.01917	0.01833	0.01395	0.00720	0.00468	0.00384	0.00330	0.00457	0.00708
1982	0.01105	0.01588	0.01879	0.01917	0.01753	0.01271	0.00723	0.00377	0.00384	0.00330	0.00457	0.00708
1983	0.01105	0.01588	0.01725	0.01561	0.01275	0.00768	0.00253	0.00065	0.00100	0.00330	0.00457	0.00708
1984	0.01105	0.01588	0.01879	0.01917	0.01959	0.01579	0.01048	0.00571	0.00384	0.00330	0.00457	0.00708
1985	0.01105	0.01588	0.01879	0.01917	0.01959	0.01523	0.00823	0.00395	0.00384	0.00330	0.00457	0.00708
1986	0.01105	0.01588	0.01879	0.01917	0.01760	0.01197	0.00550	0.00267	0.00123	0.00139	0.00332	0.00708
1987	0.01105	0.01588	0.01879	0.01868	0.01707	0.01178	0.00593	0.00254	0.00138	0.00086	0.00082	0.00708

1988	0.01105	0.01588	0.01879	0.01844	0.01649	0.01152	0.00642	0.00280	0.00165	0.00147	0.00248	0.00516
1989	0.01105	0.01588	0.01879	0.01917	0.01824	0.01470	0.00859	0.00571	0.00384	0.00330	0.00457	0.00708
1990	0.01105	0.01588	0.01879	0.01917	0.01803	0.01270	0.00610	0.00290	0.00242	0.00314	0.00457	0.00708
1991	0.01105	0.01588	0.01879	0.01873	0.01760	0.01242	0.00598	0.00247	0.00187	0.00184	0.00457	0.00708
1992	0.01105	0.01588	0.01879	0.01834	0.01637	0.01126	0.00524	0.00165	0.00110	0.00142	0.00457	0.00708
1993	0.01105	0.01588	0.01879	0.01917	0.01950	0.01462	0.00752	0.00453	0.00320	0.00300	0.00457	0.00708
1994	0.01105	0.01588	0.01879	0.01917	0.01810	0.01447	0.00837	0.00567	0.00384	0.00330	0.00457	0.00708
1995	0.01105	0.01588	0.01879	0.01917	0.01943	0.01452	0.00744	0.00446	0.00314	0.00294	0.00457	0.00708
1996	0.01105	0.01588	0.01879	0.01891	0.01705	0.01218	0.00678	0.00346	0.00384	0.00330	0.00457	0.00708
1997	0.01105	0.01588	0.01879	0.01917	0.01769	0.01278	0.00638	0.00230	0.00192	0.00330	0.00457	0.00708
1998	0.01105	0.01588	0.01879	0.01670	0.01307	0.00771	0.00264	0.00144	0.00112	0.00330	0.00457	0.00708
1999	0.01105	0.01588	0.01879	0.01828	0.01625	0.01114	0.00514	0.00160	0.00105	0.00136	0.00457	0.00708
2000	0.01105	0.01588	0.01879	0.01798	0.01550	0.01015	0.00413	0.00132	0.00054	0.00330	0.00457	0.00708
2001	0.01105	0.01588	0.01879	0.01739	0.01526	0.01027	0.00456	0.00166	0.00384	0.00330	0.00457	0.00708
2002	0.01105	0.01588	0.01879	0.01917	0.01833	0.01485	0.00873	0.00571	0.00384	0.00330	0.00457	0.00708

J.2 WRYM Precipitation for Stochastic Sequence 1

Table J.2: Precipitation from reservoir surface for WRYM (m^3/s)

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
1968	0.00398	0.00207	0.00102	0.00078	0.00053	0.00035	0.00029	0.00131	0.00714	0.00771	0.01049	0.00565
1969	0.00382	0.00186	0.00129	0.00092	0.00056	0.00044	0.00127	0.00163	0.01006	0.00725	0.00505	0.00851
1970	0.00148	0.00102	0.00087	0.00057	0.00035	0.00018	0.00016	0.00017	0.00149	0.01370	0.01046	0.01090
1971	0.00150	0.00104	0.00089	0.00058	0.00036	0.00019	0.00018	0.00020	0.00165	0.01390	0.01061	0.01106
1972	0.00171	0.00104	0.00087	0.00054	0.00034	0.00019	0.00017	0.00008	0.00000	0.01071	0.00410	0.00345
1973	0.01170	0.00400	0.00166	0.00136	0.00092	0.00058	0.00112	0.00110	0.00126	0.00164	0.00384	0.00809
1974	0.00211	0.00543	0.00657	0.00556	0.00231	0.00150	0.00152	0.01473	0.01781	0.01665	0.01607	0.00673
1975	0.00673	0.00277	0.00252	0.00255	0.00126	0.00473	0.00360	0.00445	0.01059	0.01439	0.01240	0.00595
1976	0.00149	0.00103	0.00088	0.00058	0.00035	0.00018	0.00017	0.00018	0.00155	0.01377	0.01051	0.01096
1977	0.00193	0.00480	0.00183	0.00107	0.00068	0.00044	0.00056	0.00086	0.00156	0.00567	0.00932	0.01124
1978	0.00405	0.00181	0.00103	0.00068	0.00047	0.00047	0.00029	0.00025	0.00021	0.00020	0.00029	0.00082
1979	0.00321	0.00288	0.00157	0.00185	0.00110	0.00076	0.00074	0.00236	0.00466	0.00987	0.01185	0.00512
1980	0.00319	0.00160	0.00147	0.00079	0.00058	0.00046	0.00064	0.00127	0.00119	0.00053	0.00208	0.00592
1981	0.00537	0.00295	0.00168	0.00115	0.00096	0.00061	0.00128	0.00404	0.00610	0.01466	0.00916	0.00324
1982	0.00388	0.00190	0.00141	0.00099	0.00077	0.00079	0.00082	0.00845	0.00496	0.01058	0.00624	0.01283
1983	0.00151	0.00104	0.00090	0.00059	0.00036	0.00019	0.00018	0.00021	0.00172	0.01398	0.01068	0.01113

1984	0.00661	0.00272	0.00248	0.00251	0.00124	0.00462	0.00354	0.00437	0.01040	0.01413	0.01218	0.00585
1985	0.00460	0.00286	0.00156	0.00184	0.00109	0.00075	0.00073	0.00232	0.00463	0.00980	0.01175	0.00508
1986	0.00350	0.00216	0.00150	0.00100	0.00059	0.00039	0.00056	0.00032	0.00054	0.00105	0.00583	0.00294
1987	0.00449	0.00243	0.00130	0.00097	0.00062	0.00053	0.00045	0.00041	0.00031	0.00024	0.00096	0.00627
1988	0.00494	0.00221	0.00125	0.00089	0.00065	0.00070	0.00049	0.00051	0.00057	0.00074	0.00110	0.00269
1989	0.00569	0.00354	0.00174	0.00113	0.00116	0.00096	0.00179	0.00309	0.01451	0.01245	0.00750	0.00756
1990	0.00196	0.00489	0.00187	0.00109	0.00069	0.00046	0.00058	0.00090	0.00164	0.00598	0.00949	0.01145
1991	0.00429	0.00192	0.00131	0.00106	0.00069	0.00046	0.00041	0.00065	0.00076	0.00476	0.00954	0.00569
1992	0.00553	0.00219	0.00123	0.00088	0.00061	0.00041	0.00021	0.00037	0.00054	0.00174	0.00474	0.00842
1993	0.01195	0.00408	0.00170	0.00139	0.00094	0.00060	0.00117	0.00115	0.00133	0.00174	0.00392	0.00826
1994	0.00554	0.00345	0.00170	0.00110	0.00112	0.00092	0.00170	0.00299	0.01414	0.01213	0.00730	0.00736
1995	0.01181	0.00404	0.00168	0.00137	0.00093	0.00059	0.00114	0.00112	0.00129	0.00168	0.00388	0.00817
1996	0.00370	0.00182	0.00135	0.00093	0.00072	0.00072	0.00073	0.00740	0.00473	0.01010	0.00596	0.01226
1997	0.00756	0.00274	0.00161	0.00102	0.00077	0.00053	0.00027	0.00067	0.00277	0.00815	0.01127	0.00635
1998	0.00241	0.00141	0.00089	0.00050	0.00033	0.00021	0.00032	0.00036	0.00206	0.00743	0.01149	0.00751
1999	0.00546	0.00216	0.00122	0.00086	0.00060	0.00040	0.00021	0.00035	0.00050	0.00164	0.00468	0.00832
2000	0.00381	0.00177	0.00116	0.00076	0.00049	0.00027	0.00024	0.00021	0.00150	0.00924	0.00706	0.00336
2001	0.00404	0.00210	0.00103	0.00080	0.00055	0.00036	0.00030	0.00140	0.00725	0.00784	0.01066	0.00574
2002	0.00578	0.00360	0.00177	0.00115	0.00118	0.00098	0.00185	0.00314	0.01474	0.01265	0.00762	0.00768

Appendix K

Evaporation and Precipitation for MIKE Hydro Basin

K.1 MIKE Hydro Basin Evaporation for Stochastic Sequence 1

Table K.1: Evaporation from reservoir surface for MIKE Hydro Basin (m^3/s)

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
1968	0.01105	0.01588	0.01879	0.01731	0.01525	0.01013	0.00445	0.00159	0.00384	0.00330	0.00457	0.00709
1969	0.01105	0.01588	0.01879	0.01864	0.01696	0.01138	0.00539	0.00456	0.00379	0.00330	0.00457	0.00709
1970	0.01105	0.01588	0.01715	0.01542	0.01260	0.00745	0.00237	0.00054	0.00089	0.00330	0.00457	0.00709
1971	0.01105	0.01588	0.01722	0.01555	0.01234	0.00754	0.00244	0.00060	0.00095	0.00330	0.00457	0.00709
1972	0.01105	0.01588	0.01726	0.01549	0.01249	0.00735	0.00238	0.00059	0.00000	0.00330	0.00457	0.00709
1973	0.01105	0.01588	0.01879	0.01917	0.01954	0.01445	0.00738	0.00441	0.00309	0.00288	0.00457	0.00709
1974	0.01105	0.01588	0.01879	0.01917	0.01977	0.01643	0.01048	0.00571	0.00384	0.00330	0.00457	0.00709
1975	0.01105	0.01588	0.01879	0.01917	0.01909	0.01588	0.01048	0.00571	0.00384	0.00330	0.00457	0.00709
1976	0.01105	0.01588	0.01718	0.01546	0.01266	0.00752	0.00241	0.00057	0.00092	0.00330	0.00457	0.00709
1977	0.01105	0.01588	0.01879	0.01917	0.01810	0.01259	0.00601	0.00283	0.00234	0.00304	0.00457	0.00709
1978	0.01105	0.01588	0.01879	0.01736	0.01475	0.00951	0.00472	0.00169	0.00073	0.00049	0.00079	0.00193
1979	0.00766	0.01588	0.01879	0.01917	0.01909	0.01525	0.00826	0.00398	0.00384	0.00330	0.00457	0.00709
1980	0.01105	0.01588	0.01879	0.01917	0.01672	0.01128	0.00545	0.00287	0.00313	0.00284	0.00318	0.00709
1981	0.01105	0.01588	0.01879	0.01917	0.01849	0.01396	0.00720	0.00468	0.00384	0.00330	0.00457	0.00709
1982	0.01105	0.01588	0.01879	0.01917	0.01768	0.01273	0.00723	0.00377	0.00384	0.00330	0.00457	0.00709
1983	0.01105	0.01588	0.01725	0.01561	0.01242	0.00761	0.00249	0.00063	0.00099	0.00330	0.00457	0.00709
1984	0.01105	0.01588	0.01879	0.01917	0.01977	0.01580	0.01048	0.00571	0.00384	0.00330	0.00457	0.00709
1985	0.01105	0.01588	0.01879	0.01917	0.01977	0.01524	0.00824	0.00396	0.00384	0.00330	0.00457	0.00709
1986	0.01105	0.01588	0.01879	0.01917	0.01775	0.01199	0.00551	0.00268	0.00124	0.00139	0.00333	0.00709
1987	0.01105	0.01588	0.01879	0.01868	0.01663	0.01173	0.00590	0.00252	0.00136	0.00085	0.00080	0.00709

1988	0.01105	0.01588	0.01879	0.01844	0.01664	0.01153	0.00643	0.00281	0.00165	0.00147	0.00248	0.00517
1989	0.01105	0.01588	0.01879	0.01917	0.01841	0.01470	0.00859	0.00571	0.00384	0.00330	0.00457	0.00709
1990	0.01105	0.01588	0.01879	0.01917	0.01820	0.01272	0.00611	0.00291	0.00243	0.00315	0.00457	0.00709
1991	0.01105	0.01588	0.01879	0.01873	0.01714	0.01238	0.00595	0.00245	0.00186	0.00183	0.00457	0.00709
1992	0.01105	0.01588	0.01879	0.01834	0.01652	0.01128	0.00525	0.00166	0.00111	0.00142	0.00457	0.00709
1993	0.01105	0.01588	0.01879	0.01917	0.01968	0.01463	0.00753	0.00453	0.00320	0.00300	0.00457	0.00709
1994	0.01105	0.01588	0.01879	0.01917	0.01826	0.01447	0.00838	0.00568	0.00384	0.00330	0.00457	0.00709
1995	0.01105	0.01588	0.01879	0.01917	0.01893	0.01449	0.00742	0.00445	0.00313	0.00293	0.00457	0.00709
1996	0.01105	0.01588	0.01879	0.01891	0.01720	0.01220	0.00679	0.00346	0.00384	0.00330	0.00457	0.00709
1997	0.01105	0.01588	0.01879	0.01917	0.01785	0.01279	0.00639	0.00230	0.00192	0.00330	0.00457	0.00709
1998	0.01105	0.01588	0.01879	0.01670	0.01319	0.00773	0.00265	0.00145	0.00112	0.00330	0.00457	0.00709
1999	0.01105	0.01588	0.01879	0.01828	0.01583	0.01108	0.00511	0.00158	0.00104	0.00135	0.00457	0.00709
2000	0.01105	0.01588	0.01879	0.01798	0.01564	0.01017	0.00414	0.00133	0.00054	0.00330	0.00457	0.00709
2001	0.01105	0.01588	0.01879	0.01739	0.01540	0.01028	0.00457	0.00167	0.00384	0.00330	0.00457	0.00709
2002	0.01105	0.01588	0.01879	0.01917	0.01850	0.01485	0.00873	0.00571	0.00384	0.00330	0.00457	0.00709

K.2 MIKE Hydro Basin Precipitation for Stochastic Sequence 1

Table K.2: Precipitation from reservoir surface for MIKE Hydro Basin (m^3/s)

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
1968	0.00398	0.00207	0.00102	0.00078	0.00054	0.00035	0.00029	0.00132	0.00714	0.00771	0.01049	0.00565
1969	0.00382	0.00186	0.00129	0.00092	0.00057	0.00044	0.00127	0.00164	0.01007	0.00725	0.00505	0.00851
1970	0.00148	0.00102	0.00087	0.00057	0.00035	0.00018	0.00017	0.00017	0.00150	0.01370	0.01046	0.01090
1971	0.00150	0.00104	0.00089	0.00058	0.00035	0.00019	0.00017	0.00019	0.00163	0.01390	0.01061	0.01106
1972	0.00171	0.00104	0.00087	0.00054	0.00034	0.00019	0.00017	0.00008	0.00000	0.01071	0.00410	0.00345
1973	0.01170	0.00400	0.00166	0.00136	0.00093	0.00059	0.00112	0.00110	0.00126	0.00164	0.00384	0.00809
1974	0.00211	0.00543	0.00657	0.00556	0.00233	0.00150	0.00152	0.01473	0.01781	0.01665	0.01607	0.00673
1975	0.00673	0.00277	0.00252	0.00255	0.00123	0.00473	0.00360	0.00445	0.01059	0.01439	0.01239	0.00595
1976	0.00149	0.00103	0.00088	0.00058	0.00035	0.00018	0.00017	0.00018	0.00156	0.01377	0.01051	0.01096
1977	0.00193	0.00480	0.00183	0.00107	0.00068	0.00045	0.00056	0.00086	0.00156	0.00568	0.00932	0.01124
1978	0.00405	0.00181	0.00103	0.00068	0.00047	0.00047	0.00029	0.00025	0.00021	0.00020	0.00029	0.00082
1979	0.00322	0.00288	0.00157	0.00185	0.00107	0.00076	0.00074	0.00236	0.00466	0.00987	0.01185	0.00512
1980	0.00319	0.00160	0.00147	0.00079	0.00058	0.00047	0.00064	0.00128	0.00119	0.00053	0.00209	0.00592
1981	0.00537	0.00295	0.00168	0.00115	0.00096	0.00061	0.00128	0.00405	0.00610	0.01466	0.00916	0.00324
1982	0.00388	0.00190	0.00141	0.00099	0.00078	0.00079	0.00082	0.00846	0.00496	0.01058	0.00624	0.01283

1983	0.00151	0.00104	0.00090	0.00059	0.00035	0.00019	0.00018	0.00020	0.00169	0.01398	0.01068	0.01113
1984	0.00661	0.00272	0.00248	0.00251	0.00125	0.00462	0.00354	0.00437	0.01040	0.01413	0.01218	0.00585
1985	0.00460	0.00286	0.00155	0.00183	0.00110	0.00075	0.00073	0.00233	0.00463	0.00980	0.01175	0.00508
1986	0.00350	0.00216	0.00150	0.00100	0.00059	0.00039	0.00056	0.00032	0.00054	0.00105	0.00584	0.00294
1987	0.00449	0.00243	0.00130	0.00097	0.00061	0.00053	0.00045	0.00041	0.00031	0.00024	0.00095	0.00627
1988	0.00494	0.00221	0.00125	0.00089	0.00065	0.00070	0.00049	0.00051	0.00057	0.00074	0.00110	0.00269
1989	0.00569	0.00354	0.00174	0.00113	0.00117	0.00096	0.00179	0.00309	0.01451	0.01245	0.00750	0.00756
1990	0.00196	0.00489	0.00187	0.00109	0.00070	0.00046	0.00058	0.00090	0.00165	0.00599	0.00949	0.01145
1991	0.00429	0.00192	0.00131	0.00106	0.00068	0.00046	0.00041	0.00064	0.00075	0.00473	0.00954	0.00569
1992	0.00553	0.00219	0.00123	0.00088	0.00061	0.00041	0.00021	0.00037	0.00054	0.00174	0.00474	0.00842
1993	0.01195	0.00408	0.00170	0.00139	0.00095	0.00060	0.00117	0.00115	0.00133	0.00174	0.00392	0.00826
1994	0.00554	0.00345	0.00170	0.00110	0.00113	0.00092	0.00170	0.00299	0.01414	0.01213	0.00730	0.00736
1995	0.01181	0.00404	0.00168	0.00137	0.00091	0.00059	0.00114	0.00112	0.00129	0.00168	0.00388	0.00817
1996	0.00370	0.00182	0.00135	0.00093	0.00073	0.00072	0.00074	0.00741	0.00473	0.01010	0.00596	0.01226
1997	0.00757	0.00274	0.00161	0.00102	0.00077	0.00053	0.00027	0.00067	0.00278	0.00815	0.01127	0.00635
1998	0.00241	0.00141	0.00089	0.00050	0.00033	0.00021	0.00032	0.00036	0.00207	0.00743	0.01149	0.00751
1999	0.00546	0.00216	0.00122	0.00086	0.00058	0.00040	0.00020	0.00035	0.00050	0.00163	0.00468	0.00832
2000	0.00381	0.00177	0.00116	0.00076	0.00049	0.00027	0.00024	0.00021	0.00152	0.00924	0.00706	0.00336
2001	0.00404	0.00210	0.00103	0.00080	0.00055	0.00036	0.00030	0.00141	0.00725	0.00784	0.01066	0.00574
2002	0.00578	0.00360	0.00177	0.00115	0.00119	0.00098	0.00185	0.00314	0.01474	0.01265	0.00762	0.00574